IMPROVING THE COST MODEL DEVELOPMENT PROCESS USING NEURAL NETWORKS

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Abstract

In order to achieve success in export markets through provision of high levels of product choice, manufacturing industry will need to develop and economically use many new materials and manufacturing processes. To support this development, it is expected that the quantity, type, accuracy and complexity of cost models will need to be greatly increased. It is essential under these changing conditions that the process of developing cost models is able to remain responsive to user requirements and effective in terms of the resources required to generate models.

This research investigates existing methods of establishing 'cost estimating relationships' and identifies their relative benefits and limitations in terms of their effects on the overall cost model development process. The basic tasks involved in the cost model development process and the basic characteristics of cost models have been identified and used to evaluate the use of Artificial Neural Networks (ANNs) as alternative methods of establishing cost models. The problem of identifying suitable ANN structures has been resolved by the use of the Taguchi Methodology. Experiments to identify the influence of varying the number of layers and number of processing elements per layer within an ANN structure have shown that in general, increasing the number of processing elements per layer and decreasing the number of layers leads to increased estimating accuracy. Experiments to examine the effects of varying the amount of data used to develop the model and varying the number of variables within the model have indicated that substantial benefits, in terms of simplifying data identification and collection tasks can be realised when compared with regression analysis.

Acknowledgements

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Finally, I must thank my parents for all their memorable support and encouragement, which is too precious to forget.

Declaration

I declare that the work described within this thesis was originally undertaken by myself, (Qing Wang) between the dates of registration for the degree of Doctor of Philosophy at De Montfort University, February 1998 to November 2000.

Table of Contents

List of Figures

List of Tables

Glossary

A	Effective Area to be Machined
Abs Error	Absolute Error
ANNs	Artificial Neural Networks
ART	Adaptive Resonance Theory
BP	Back Propagation
B_s	Batch Size
CAD	Computer Aided Design
CERs	Cost Estimating Relationships
d_m	Density of the Work Material
HD	Hole Diameter
l_r	Length/Diameter Ratio of the Work Piece
M.O.S.T	Maynard Operation Sequence Technique
MTM	Methods Time Measurement
n	Taylor Tool Life Index
NL	Number of Layers
n_0	Number of Operations
n_t	Number of Tools
OA	Orthogonal Arrays
PE	Processing Element
P_s	Specific Cutting Energy or Unit Power for the Work Material
r_e	Proportion of Material Removed by External Machining
r_i	Proportion of Material Removed by Internal Machining
R_{sg}	A Machinability Factor
r_v	Proportion of the Initial Volume
SR	Speed of Drill
TanH	Hyperbolic Tangent
Th	Thickness of Hole being Drilled
$t_{\ln}$	Loading and Unloading Time
t_{mc}	Finish Machining Time
$\boldsymbol{t_{mp}}$	Machining Time for Roughing Operations
$\boldsymbol{t_{np}}$	Non-Productive Time
t_{pt}	Tool Positioning Time per Operation
t_{sa}	Basic Set-up Time for Machine
t_{sb}	Set-up Time per Tool
W	Weight of the Work Piece

Chapter 1 Introduction

1.1 The Cost Modelling Environment

Market trends suggest that UK industry (De Rosa, 1999; Stalk and Hout, 1990; Wooding, 1997), in order to secure significant future export sales, will need to address the requirements listed in Table 1.1.

Provide Greater Choice of Products
Provide Greater Amounts of Product Customisation
Provide Greater Choice of Materials
Provide Greater Choice of Manufacturing Processes
Provide Reduced Product Development Cycles
Provide Greater Emphasis to Minimising Overall Life Cycle Costs of Products
Provide High Return on Investment Products

Table 1.1 Main Effects of Market Requirements

In order to support the product and process development needed to meet these market expectations, it is expected that the quantity, type, accuracy and complexity of cost information to be generated will need to be greatly increased. These changes will have a dramatic effect on the cost estimating process. This effect will arise due to the nature of the cost estimating process, which involves both costly and time-consuming tasks that require high levels of process and product expertise to arrive at valid cost estimates. Cost models are an essential part of the overall cost estimating process in that they are important methods of deriving cost and process time information. The changes affecting the market environment will have similar effects on both the cost estimating and cost modelling processes as shown in Table 1.2.

	Limitations on Cost Estimating/Modelling Processes				
Changes Occurring in the Market Environment	Greater Number of Cost Models Required	Less Historical Cost Data Available	Less Time Available to Develop Models	Greater Product & Process Complexity	Less Process Expertise Available
Greater Choice of Products	√	√			√
Greater Amounts of Product Customisation	√	√	√	√	√
Greater Choice of Materials	√	√		√	√
Greater Choice of Manufacturing Processes	√	√		√	√
Reduced Product Development Cycles		√	√		
Greater Emphasis Placed on Life Cycle Costs	√	√		√	

Table 1.2 Examples of Effects on Cost Estimating/Modelling Processes

As with cost estimating, the cost model development process is often time consuming and hence unresponsive to users needs for cost information. The process, therefore, frequently requires high levels of resources to achieve a satisfactory outcome. These problems, in part, result from a lack of effective tools and techniques for enabling experienced engineers to select and apply appropriate cost model development practices. In addition, within the development process, there are significant shortfalls in the data identification, data collection, data analysis and decision making tools available to cost engineers. A potential constraint to providing this support for product and process development in an effective and timely manner would, therefore, be the cost modelling process itself. The main tasks involved in the development of a cost model, i.e. data identification, data collection and data analysis will all be effected by the constraints placed on the cost estimating and cost modelling processes as indicated in Table 1.3.

	Limitations on Cost Estimating /Modelling Processes				
Cost Model Development Tasks	**Greater Number of Cost Models Required**	**Less Historical Cost Data Available**	**Less Time Available to Develop Models**	**Greater Product & Process Complexity**	**Less Process Expertise Available**
Data Identification	√	√		√	√
Data Collection	√	√	√	√	√
Data Analysis	√	√	√	√	√

Table 1.3 Examples of Effects on Cost Model Development Tasks

Of particular concern are the mathematical modelling techniques used to establish the 'cost estimating relationships' (CERs) which form the basis of cost models. The characteristics which describe these CERs will all be affected (i.e. Table 1.4) by the constraints imposed by the changing market trends indicated in Table 1.1.

Cost Model Characteristics	Limitations on Cost Estimating/Modelling Process: Greater Number of Cost Models Required	Less Historical Cost Data Available	Less Time Available to Develop Models	Greater Product & Process Complexity	Less Process Expertise Available
Accuracy		√	√	√	√
Type of Input Data	√	√	√	√	√
Detail of Input Data	√	√		√	√
Subjective Judgement	√	√		√	√
Personnel	√	√		√	√
Operating Costs		√		√	√
Set-up Costs		√	√	√	
Response Times	√	√		√	

Table 1.4 Examples of Effects on Cost Model Characteristics

1.2 Aims and Scope

The principal aim of this research is to improve the speed and effectiveness with which cost models can be developed and applied. This aim will be achieved by identifying and examining traditional mathematical modelling techniques used to establish CERs and determining their relative advantages and limitations. It is then the intention of the research to examine the potential for using artificial neural network procedures (Wang and Stockton, 1999) for developing cost models and to establish rules for designing appropriate artificial neural network structures (Wang and Stockton, 2000) for costing applications. The artificial neural network (ANN) methods developed must be capable of forming part of a coherent cost model development process (Stockton, Forster and Messner, 1998). Hence, the effectiveness of ANN procedures developed will need to be related not only to their ability to assist individual cost model development tasks but also their ability to generate methods that possess specific cost model characteristics.

The current research work is aimed at identifying robust ANN structures through use of the Taguchi Methodology. In addition, a range of experiments will be carried out to establish the effects, on both cost model characteristics and cost model development tasks, of such factors as number of hidden layers, number of processing elements per layer, number of data points used to develop the model and the number of variables within the model.

1.3 Structure of Thesis

In order to achieve these aims, the remaining thesis is organised as follows:

Chapter 2 provides an overview of the current state of cost estimation for manufacturing. It begins by examining the cost estimating process and identifies, within this process, the role of cost models. The effectiveness of several common techniques for estimating process times is then examined in terms of their ability to cope with the changes that are occurring in the manufacturing environment. The analysis, provided in Chapter 2, indicates that cost estimating methods in current use are unable to provide cost information quickly and economically since they are both time consuming, complex and require high levels of process expertise. Chapter 2 identifies artificial neural networks as a potential method of improving the cost modelling process.

Chapter 3 initially provides an introduction to the development of the technology underpinning artificial neural networks and then continues by describing the functions of the basic types of layers, i.e. input, hidden and output, and how these layers form the basic structure of all artificial neural networks. A review is then provided of recent applications of artificial neural networks within the manufacturing domain. Although it is acknowledged that artificial neural networks have generated much research interest in the manufacturing area, many of the applications reported in the literature have been found to be either laboratory experiments or preliminary applications. A review and discussion is also provided of the particular application of artificial neural networks within the cost estimating domain.

A more detailed study is carried out of the 'processing element', which forms the heart of most artificial neural networks and the various function types associated with these processing elements. These function types provide artificial neural networks with the ability to model a wide variety of relationships between input and output variables. A central theme highlighted by the research literature is that of the difficulties involved in the selection of the most appropriate network structure for individual applications. Chapter 3 then presents the direction of the current research, which is to develop a methodology for identifying best ANN structures. The chapter ends by identifying the benefits and limitations of using artificial neural networks for developing cost models. This is carried out with reference to the individual characteristics of cost models, i.e. range of application areas, estimating accuracy, user personnel, set-up and operating costs, and data requirements.

Chapter 4 briefly describes the proposed ANN methodology and the need to perform cost modelling trials to identify the rules used to develop suitable artificial neural network structures for specific costing applications.

Two application areas have been selected for identifying the potential for using ANNs to develop cost models and these are initially described in Chapter 3. The first manufacturing process examined was that of 'turning' which as a costing problem is representative of a range of costing applications that normally need to be costed in great detail. The variables that influence the time, and hence cost, of the turning operation included both linear & non-linear relationships, manual & machine related activities, batch & non-batch related activities and direct & non-direct cost types. Hence, this application represents a difficult challenge to any modelling technique. The second area selected was the drilling process, which represented a major process involved in the aerospace industry. Details of the experimental design are then provided along with background information on the Taguchi methodology, which is used to design the experimental trials.

The Taguchi Methodology is used primarily to identify 'best' and 'worst' ANN structures. The models developed using these structures are then used for further trials designed to investigate the influence of data quantity on the estimating accuracy of models, i.e. by varying the number of data points used in a cost model's development and varying the number of predictor variables within models. Regression based models are used to compare the estimating accuracy obtained from the thesis.

Chapter 5 presents the results of the experimentation and an analysis of these results.

Chapter 6 discusses the needs for this research and summarises the overall approach and research methodology, including the knowledge gained from the review of literature and the implication to the cost modelling process of the experimental results reported and analysed in Chapter 5. Conclusions and future research directions are provided in **Chapters 7** and **8.**

Chapter 2 Developing Cost Models

2.1 Cost Estimating

2.1.1 Introduction

Cost estimating (Ostwald, 1988) is the process of calculating the expected cost resources, i.e. labour, material and overhead costs, which are required to accomplish a manufacturing task or to manufacture or purchase a specific product. It is necessary to understand the cost estimating process since cost models are an essential part of this process in that they are important methods of deriving cost and process time information.

The basic guidelines for cost estimation in manufacturing businesses are provided by Ostwald (1988), Cunningham and Dixon (1988), and Chang (1990). In general the process of developing a cost estimate can be divided into the basic steps shown in Figure 2.1.

The initial tasks involved in cost estimation are dependent on the products made, the manufacturing processes used, and the specific accounting methods employed by individual business organisations. Within manufacturing industry there are a wide variety of manufacturing processes and accounting methods in use. Personnel undertaking a cost estimating exercise must ensure they have expertise in the particular processes and accounting methods used by the specific company for which the exercise is being undertaken.

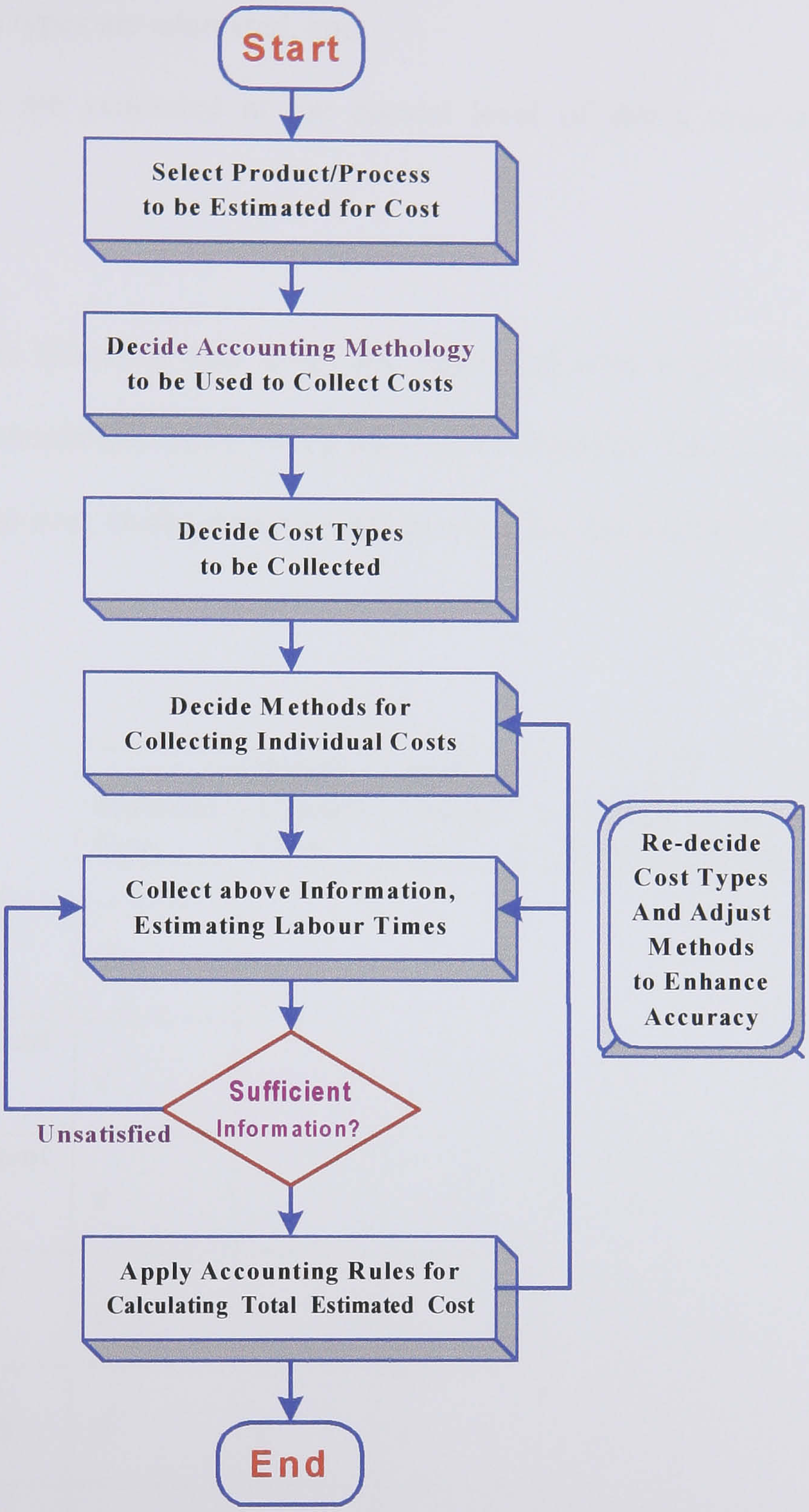

Figure 2.1 Basic Cost Estimating Process

Decisions concerning the cost types and resources to be estimated, (Table 2.1 (Stockton, 2000)), must consider the basic business decisions that they are required to help make, (Table 2.2 (Stockton, 2000)), in order to ensure that:

a. correct cost types are estimated, and

b. these costs are estimated at the correct level of detail required to make decisions.

It is important that following this stage the remaining cost estimation process is directed towards successfully ascertaining these cost resources. This stage also forms the beginning of the cost model development process for the product and/or process selected.

		Material Cost	Direct Labour Cost	Indirect Labour Cost	Process Time	Elapsed Time	Manning Levels
Product Resource Costs	**Product Level**	√					
	Component Level	√					
	Component Feature Level	√					
Process Feature Costs	**Machine Level**	√	√	√			
	Machine Assembly Level	√	√	√			
	Sub-Assembly Level	√	√	√			
Process Activity Cost	**Process Level**		√	√	√	√	√
	Process Operation Level		√	√	√	√	√
	Operational Activity Level		√	√	√	√	√

Table 2.1 Basic Types of Cost Resources

Cost reduction
Process Time Reduction
Process Evaluation
Process Improvement
Process Development
Product Evaluation
Product Improvement
Product Development
Standard Data Generation
Capacity Planning
Production Scheduling
Pricing and/or Quotations
Business Planning
Investment Planning
Procurement Decisions
Manufacturing Decisions

Table 2.2 Basic Business Objectives

There are a variety of methods available for collecting individual costs, examples of which are listed in Table 2.3 (Stockton, 2000), which to ensure accuracy of estimates, must primarily involve the use of experienced cost engineers. During this stage of cost estimating it is necessary, if manufacturing costs are being estimated, to define and plan the work performed in as much detail as required to develop the necessary accuracy of cost estimates required. In order to perform this task it is advantageous to establish an estimating team. This team should contain sufficient expertise to enable determination of the purpose, scope, and time constraints for developing the estimate, analysis of the details of the work to be done, and identification of the types and quantities of materials, parts and equipment required.

Observation of Process
Interview Experts
Manual Analysis of Records
Computer Analysis of Records
Experimentation
Charting
Brainstorming
Sampling
Simulation
Questionnaire
Data Mining
Case Based Reasoning
Cause & Effect diagrams
Team Working
Comparing with Existing Cost Estimates

Table 2.3 Examples of Data Collection Methods

The cost elements or functional areas, such as engineering, manufacturing and procurement, required to perform the work must then be identified and a schedule prepared of the work and the level of effort defined and identified. This stage also involves selecting an appropriate cost/process time estimating methodology, the main categories of which are shown in Figure 2.2 (Wild, 1985) and use of this method to estimate the man hours, material costs, and other cost generating variables. In addition, the elapsed time required to perform each detail of the work must be determined. Cost rates are then identified and used to establish the relevant costs of work elements.

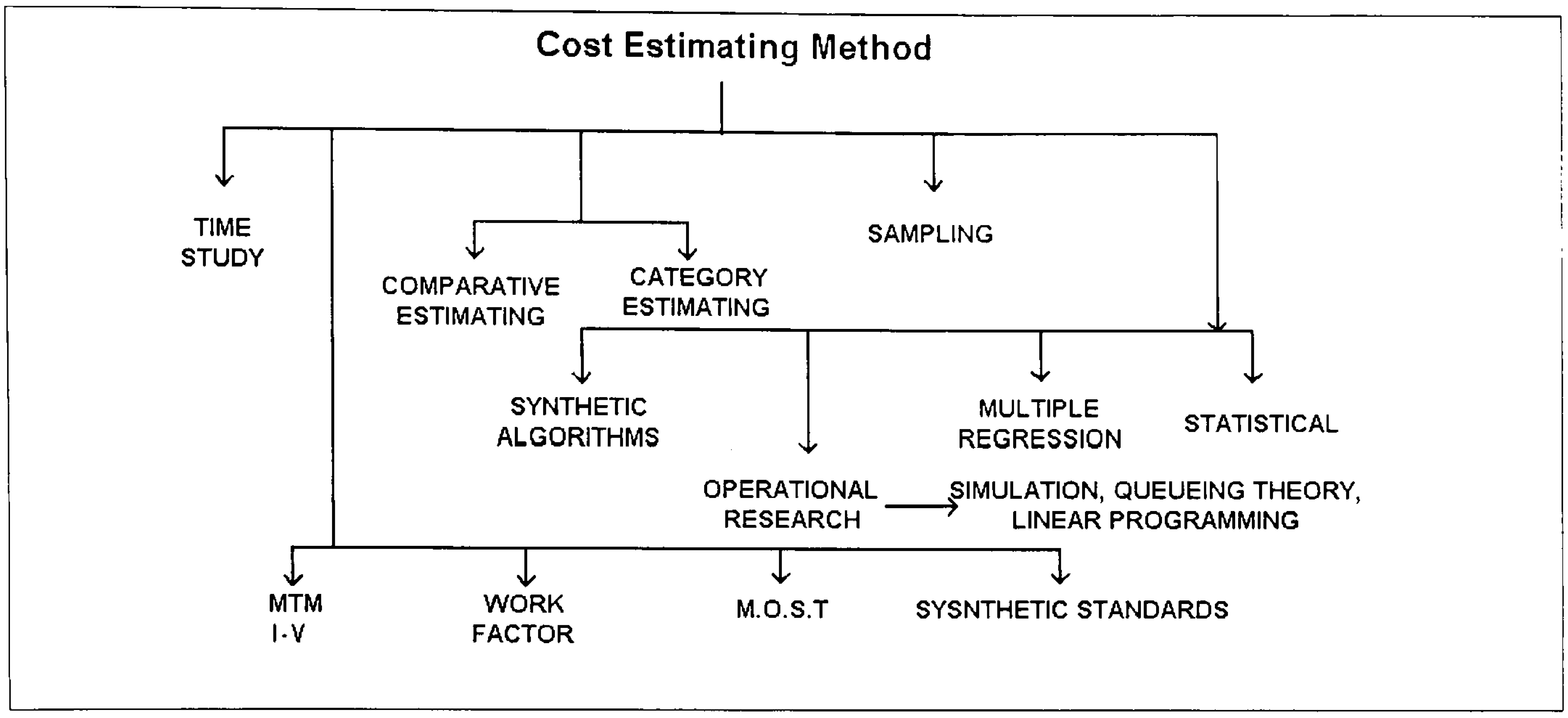

Figure 2.2 Cost Estimating Methods

Each time a new estimate needs to be developed or updated the above tasks must normally be repeated unless some form of comparative estimating technique is being employed. These tasks are both labour and time intensive and make the cost estimating process not only costly but also unresponsive to many of the needs of such functions as product and process development. The cost modelling process makes use of the above tasks but with differing objectives, i.e. the primary objective is to collect appropriate cost, product and process data such that the basic relationships can be established, between costs and the product and/or process variables that drive these costs. Once these relationships have been established, normally in the form of mathematical equations, users need merely to input appropriate values of product and/or process variables and the cost model outputs the relevant costs. Hence, the need to repeat a costly and time intensive cost estimating process may be avoided.

When using either cost estimating or cost modelling, the next step is to apply the accounting procedures, initially selected, to the basic estimated cost or process time to establish the final cost estimate. The cost estimation process itself must be sufficiently robust and transparent to withstand close scrutiny from both internal and external users of the costs such as other internal functional departments and external customers. In addition, successful updating of the estimate also depends on the level of traceability involved in the estimating processes and data sources used. The level of traceability can be severely affected depending on the amount of judgement or subjective opinion on the part of the estimator that is required during the development of a cost estimate. This also needs to be considered when developing and using cost models.

Although Figure 2.1 suggests that the process steps involved in cost estimation are sequential, in reality, the process is iterative, and individual steps often occur out of sequence or repeatedly throughout the estimating process. For instance, for an estimate to be useful and realistic, the estimator must involve and appraise management throughout the process, and not present only the final estimate.

Once the appropriate cost data has been collected the actual cost estimates can be developed through a variety of estimating methodologies, (Figure 2.2), which may be applied individually, or in combination, depending on the information and resources available to the cost estimator.

In terms of manufacturing, each of these methods requires an analysis of the work task to be performed and each can vary in the level of detail required in the definition of the work to be performed. To determine the costs of manufacturing a product or the costs involved in operating a specific production process, it is necessary to identify cost elements and choose an appropriate method of estimating each type of cost. In this respect the majority of cost estimates are normally compiled by utilising a combination of past similar product costs, established in-house cost knowledge and/or published cost information. Published cost information can reduce the cost and time of establishing costs. Such information includes cost indexes, which allow estimates to be adjusted to present industrial environments. For example, Marshall and Swift Equipment Cost Indexes (Venkatachalam, 1990) are compiled for over forty different industries. However, existing cost information is of restricted use when attempting to estimate the cost of new manufacturing technology.

2.1.2 Comparison of Cost Estimating Methods

	Constraints on Costing Products and Processes				
	Greater Number of Models Required	**Less Historical Cost Data Available**	**Less Time Available to Develop Models**	**Less Process Expertise Available**	**Greater Process & Product Complexity**
Time Study	C_1	C_2	C_1	C_3	C_1
MTM	C_1	C_2	C_1	C_3	C_1
Comparative Estimating		C_4			C_4
Category Estimating				C_3	C_3

Key: Constraints to Establishing Product and Process Costs

C_1	Requires Large Amounts of Time
C_2	Requires Observation of Actual Process
C_3	Requires Availability of Process Experience
C_4	Requires Large Amount of Historical Cost Data

Table 2.4 Comparison of Cost Estimating Techniques

A comparison, Table 2.4, of several common techniques for establishing process times indicates that there is a deficiency in their ability to cope with the changes occurring in the manufacturing environment Tables 1.1 and 1.2.

2.2 Applications of Cost Models

The majority of cost modelling research has been directed at the development of cost models for assisting the product design process either by:

a. aiding the identification of low cost design options (Sanchez et al, 1998; Yeo, Ngoi & Chen, 1998; Gutman, 1981),

b. supporting design for manufacture and design for cost environments (Lee & Young, 1994; Eversheim, Neuhausen & Sesterhenn, 1998; Bavishi, 1997; Dean, 1990; Gatois & Morris, 1999), and

c. supporting a concurrent engineering environment (Dick, 1993).

Bavishi (1997) identifies the following uses, other than to cost jobs, of cost estimates, i.e. produce routings, aid process planning, forecast capital investment, predict labour requirements and identify hidden, unnecessary costs.

In addition, there have been a wide variety of other applications for cost models including those developed for use during:

a. factory construction when determining the production capacity required (Ito, Ogawa and Tani, 1996),

b. machine time estimation for magnetic abrasive processes (Kremen, Elsayed and Ribeiro, 1994),

c. costing the design of software systems (Weyuker, 1999; Burnett, 1996),

d. applications involving electronic manufacture and assembly (Teng and Garimella, 1998; Miles, 1988; Bloch and Ranganathan, 1991),

e. condition based overhaul and replacement of equipment (Thorstensen and Rasmussen, 1999),

f. foundry, construction and mining industries (Bidansa, Kadidal and Billo, 1998; Sha'at, 1993; Cebesoy, 1993),

g. project cost estimating (Mulkezi, 1994), and

h. estimation of life cycle costs (De Vasconcellos and Yoshimura, 1999; Hegde, 1994).

There has also been much research interest focused on the construction of quality cost models and their application in manufacturing and process industries. Dale & Plunkett (1991), Porter & Rayner (1992), and Elsen & Followell (1993) have provided reviews of the various quality cost models used within total quality management environments. Hwang and Aspinall (1996) critically appraised several quality models together with details of their applications and analysed the current gap between theory and practice. The results of their analysis revealed that:

a. each of the main cost modelling philosophies possessed limitations in its use, i.e. either they were useful at a process level in explaining the causes of quality problems or they were more applicable at relating quality costs to strategic planning at an organisational level,

b. cost models could only be transferred from one organisation to another within the same industry, and

c. cost models only reflected internal quality costs and not those of external organisations such as customers or suppliers hence preventing the integration of quality costs into the strategic plan.

This work has important implications for the development of all forms of cost models since the same limitations can apply if care is not exercised during the cost model development process. For example, efforts must be made, where applicable, to ensure that the correct level(s) of cost models are developed such that they are applicable at the appropriate level in the organisational structure and at the appropriate level of decision making, i.e. strategic, tactical and operational. The failure of quality cost models to reflect external quality costs normally arises because of the extreme problems in obtaining any form of cost information from either customers or suppliers. This problem is also inherent when developing any type of cost model.

2.3 Cost Model Characteristics

In order to ensure that appropriate data is collected from which the cost model can be derived it is necessary, initially, to establish the characteristics of the cost model. These characteristics and their inter-relationships are shown in Figure 2.3 (Stockton, Forster and Mesner, 1998).

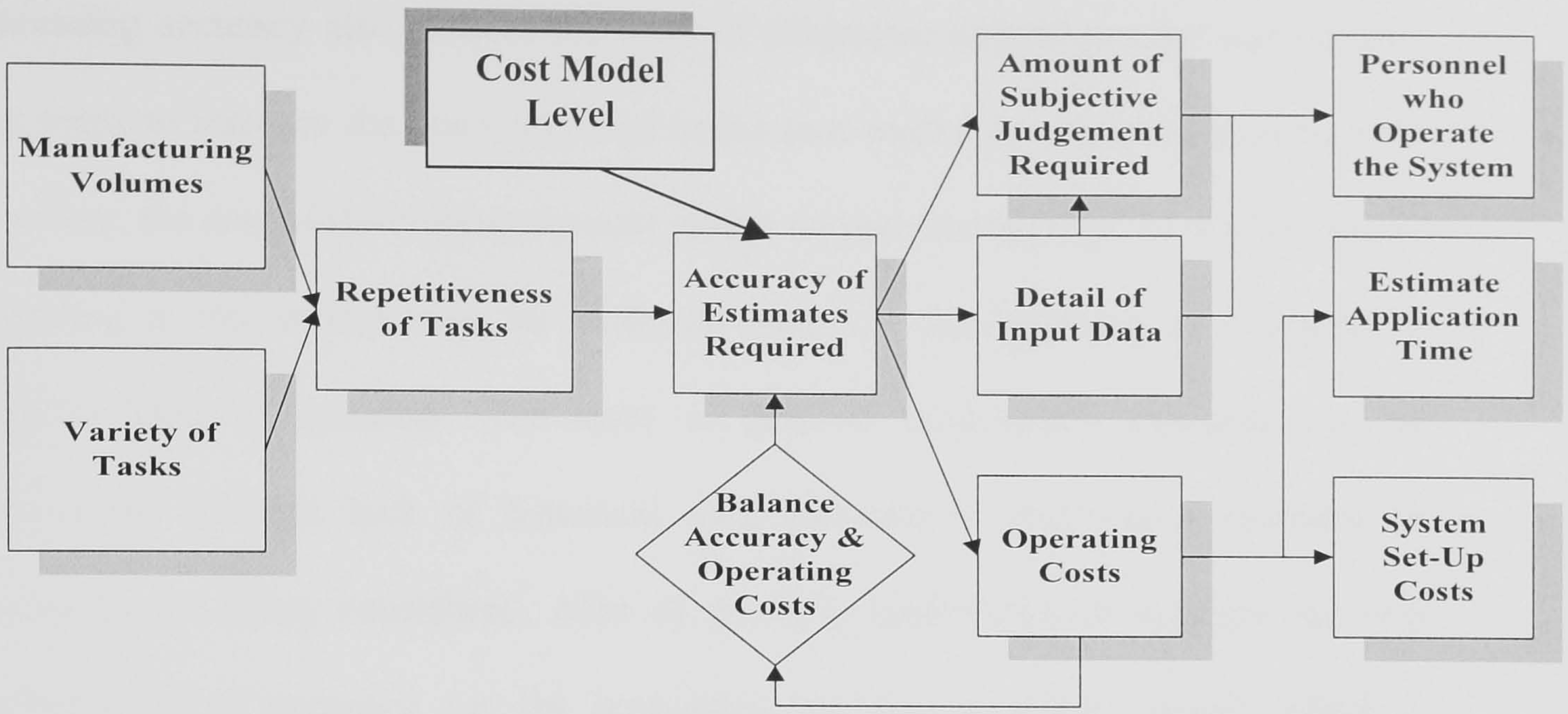

Figure 2.3 Inter-Relationships Between Cost Model Characteristics

Figure 2.3 indicates that the variety in the type of tasks used within a company and their manufacturing volumes will influence the repetitiveness of individual tasks. In particular it is the repetitiveness of an individual task that determines the accuracy with which cost estimates are required. The greater the repetitiveness of an individual task then the greater must be the accuracy with which it is costed, i.e. to avoid even small cost differences being magnified into large cost variances. In terms of accuracy Park (1973) states that "the cost estimate can within certain limits be made as accurate as the engineer's company or client is willing to pay for".

The level of accuracy required from a cost model will determine to a large extent the operating costs, i.e. the cost of establishing a cost estimate. For example, in order to improve estimating accuracy it may be necessary to increase the level of detail to which manufacturing tasks are broken down in order to employ detailed work measurement techniques such as Methods Time Measurement (MTM) (Mundel, 1978; Currie, 1977).

Increasing accuracy also reduces the level of subjective judgement that can be used and tends to increase the costs involved in the cost model development process and, therefore, the cost of developing the cost model. In practice the costs of setting-up and operating a cost model must be balanced with the consequences of accepting a specific level of accuracy. The level of detailed information available can be constrained through lack of historical data particularly when new products or processes are being considered. Also of growing importance to industry are two further types of accuracy, i.e. the estimating precision of a cost model, which is important when comparing alternative processes and the costing tolerances that can be achieved through using a model. The latter type is a measure of the risk involved in using the estimates produced by a model.

Ideally an effective data analysis technique, such as artificial neural networks, must assist in enabling the constraints to the development of cost models to be overcome and in addition be capable of meeting the user needs in terms of the required characteristics of the cost model.

2.3.1 Cost Model Levels

Figure 2.3 also indicates that the level of cost model required determines the accuracy required from cost models. Within industry the basic levels of cost models employed are as follows:

(i) **High Level Model** - where relatively simple data inputs are required to yield costs for complete subsystems or whole products. A low level of cost detail is provided by such models. These models are normally used at strategic or concept decision-making stages and typical inputs would be in terms of the expected weight or dimensions of a product. Ballpark estimates would then be output suitable for quickly establishing the viability of alternative concepts.

(ii) **Low Level Model -** requires in-depth examination of the process or product to be costed. The detailed activities of the manufacturing process must be identified for each individual component that makes up a product and the relationships between these activities and the cost resources required to perform them. Low level models tend to be highly accurate and are used for such functions as the detailed costing of components or comparison of alternative detailed designs. In order to develop low level manufacturing process cost models a thorough understanding of the manufacturing processes involved is required. They are based on a detailed estimation of the main manufacturing cost categories such as material use, fabrication and assembly.

These types of models also focus on labour, process time and cost. Figure 2.4 illustrates the relationship between labour/process time and other cost elements.

The cost of labour includes the direct labour time and cost rate for the product. The determination of these values will require a thorough knowledge of the operations performed, and the sequence of operations, machines and tools used. Although a proportion of these costs will be included in the overhead costs the cost estimator must be certain that all costs are included.

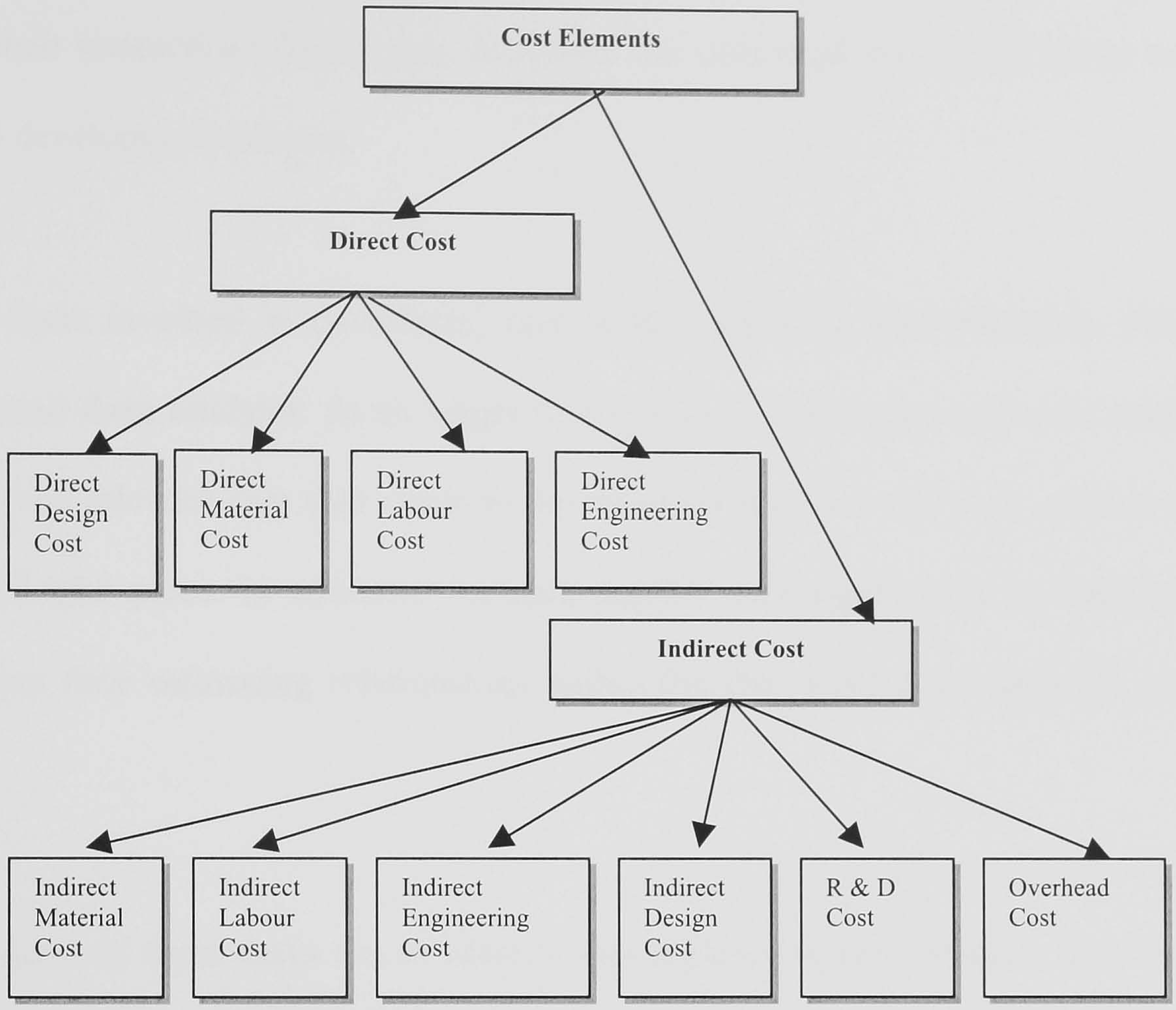

Figure 2.4 Relationship Between Labour/ Process Time & Other Cost Elements

(iii) **Heuristic/Rule of Thumb Model** - these models involve cost estimators and/or process experts providing subjective estimates of the relationships between products and/or processes and their costs. The accuracy of such models depends on the levels of experience and bias of the persons making the estimates.

2.4 Cost Model Development Process

At each of the levels described in Section 2.3.1 cost models can be described in terms of the common set of characteristics shown in Figure 2.3. It is these characteristics, e.g. estimation accuracy, level of detail of input and output data, estimate application time, and their interactions that largely determine the individual tasks involved in the cost model development process.

The basic tasks involved in developing cost models are **data identification, data collection and data analysis**. At all stages in the process, decisions need to be made concerning the relevant data that needs to be collected and how this data collection process will take place. In addition, the data analysis techniques used to establish valid process time estimating relationships within the data need to be selected and applied.

The basic aims of these tasks are to identify and collect product, process, cost and time information and to analyse this information in order to quantify the cost estimating relationships that exist. The importance of adopting an effective model development process has been examined, with respect to cost models, by Lederer and Prasad (1993) who identified that the model development process itself was mainly responsible for causing inaccuracy in estimates. In terms of the individual techniques and tools used for data identification, collection and analysis significant improvements have occurred since Stockton (1983) developed a cost estimating system for use by designers within a major UK crane manufacturer. However, the basic cost model development processes in current use within manufacturing industry have remained relatively unchanged to that used within this work.

Previous work (Stockton and Wang, 1999) outlined how several advanced modelling techniques, including artificial neural networks, could potentially provide methods for successfully overcoming the constraints to the development of cost models. In order to achieve this aim these methods must assist in:

a. identifying cost drivers and their relative importance,

b. significantly reducing the amount of data required to establish models,

c. reducing the required accuracy of input data and where possible enable greater levels of qualitative data to be used,

d. removing the need to establish the variables that constitute the cost drivers,

e. removing the need to know prior to data analysis the form of the cost function, and

f. increasing the number of variables that can be considered within the cost model.

Building on the work of Busch (1994) and Clark (1985) the process illustrated in Figure 2.5 (Stockton, Forster and Mesner, 1998) has been developed as the focus of an EPSRC funded (Grant Ref. GR/M58818) research programme entitled "Improving the Cost Model Development Process. The primary objective of this project is to improve the basic cost model development process. An essential aim within this work is to identify 'best practice' cost modelling techniques used in industry and where necessary developing tools to meet identified gaps in this 'best practice' provision.

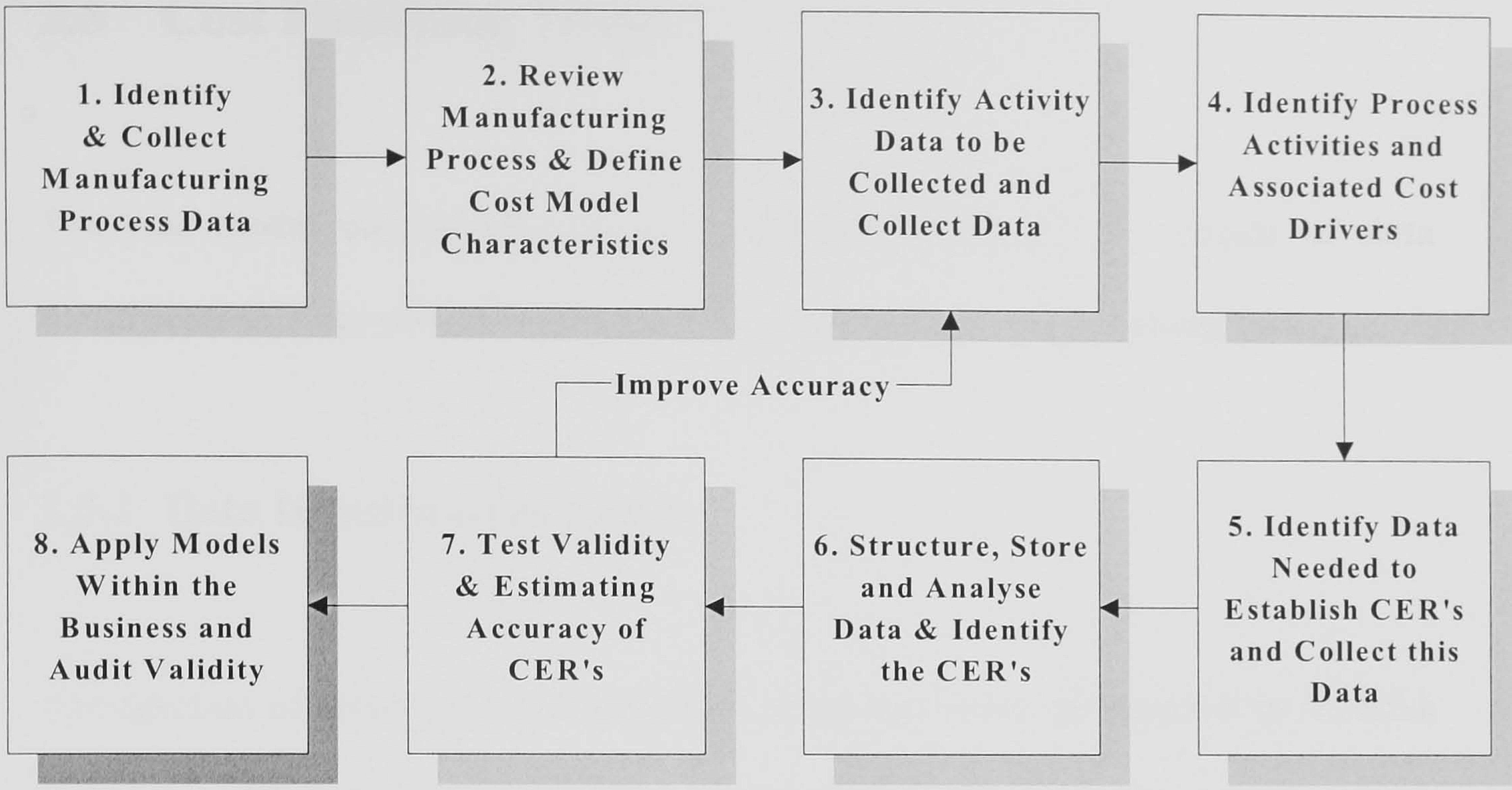

Figure 2.5 Cost Model Development Process

An additional objective of the work is to improve the speed and efficiency with which cost models can be developed as well as overcome the causes of inaccurate estimates encountered by Lederer and Prasad (1993), in particular:

a. users' lack of understanding of their own requirements,
b. insufficient user-analyst communication and understanding,
c. imprecise problem definition and insufficient analysis when developing an estimate,
d. lack of an adequate methodology or guidelines for estimating,
e. insufficient time for testing, and
f. lack of participation in estimating by the systems analysts and programmers who ultimately develop the system.

2.5 Cost Modelling Tasks

The cost model development process illustrated in Figure 2.5 consists of **data identification, data collection, and data analysis and decision making tasks**, i.e.:

2.5.1 Data Identification Tasks

The function of these tasks is to determine what data items are required to establish the cost model. Data identification occurs at several stages within the overall process. These stages include identifying the data needed to review the process and establish the cost model characteristics, identifying what the basic process activities are and identifying the detailed data needed to establish the cost estimating relationships. In order to overcome the constraints listed in Table 1.3 the methods used to identify data must be able to:

- **a.** identify potential cost drivers with minimal information,
- **b.** rank cost drivers (Turney, 1991) in order of importance with minimal information,
- **c.** reduce the dependence on expert knowledge for identifying cost drivers, and
- **d.** select relevant data items from amongst many, i.e. choosing from amongst alternatives.

2.5.2 Data Collection Tasks

The function of these tasks is to capture relevant data. Hence, they must address such issues as where will the data be obtained from, who will collect the data and when will the data be collected. The methods used to collect data must be able to:

a. minimise the time and resources required to collect data,

b. ensure that the correct data is obtained, and

c. ensure that data is both accurate and valid.

The input data needed to develop and use cost models (Hundal, 1993; Dhavale, 1990) can be grouped into the following basic areas:

a. economic parameters, i.e. such as wages, working days per year that can be determined by the location of the plant and its related environmental factors,

b. design specifications, i.e. part dimensions, materials which are driven by the product design (Dewhurst and Boothroyd, 1988) of the investigated system, and

c. production parameters, i.e. parts per year, scrap rate, cycle time.

On the basis of the production volume and the available production capabilities the needed capacity of production is estimated. This estimation includes scrap rates, material types, and assembly operations. The cost of each process step is calculated by its resource consumption. Finally the costs of the entire production are accumulated to the overall costs per operation, to the overall costs per constituting cost elements and per component.

2.5.3 Data Analysis Tasks

The function of these tasks is to establish the cost estimating relationships (CERs) from the data collected. The methods used to establish the CERs must be able to:

- **a.** remove the need to establish the variables that constitute the cost drivers,
- **b.** remove the need to identify the relative importance of each cost driver,
- **c.** remove the need to know the form of the cost function,
- **d.** increase the number of variables that can be considered simultaneously,
- **e.** remove the need for quantitative data by increasing the use of qualitative data,
- **f.** decrease the accuracy of the data items required,
- **g.** reduce the level of data required,
- **h.** increase the accuracy/data detail ratio, i.e. obtain improved accuracy with lower level of data detail,
- **i.** where possible automate data collection tasks, and
- **j.** remove the need to formally structure data.

2.5.4 Data Management Tasks

The function of these tasks is to structure, store and retrieve data in a manner suitable for data analysis and when required for providing confidence in the ability of individual cost models. Here it is important that data analysis methods allow the validity of models to be audited.

2.5.5 Data Quality Procedures and Auditing Procedure Tasks

The function of these tasks is to test the validity of the established cost models and estimating accuracy of CER's. Here it is important that the validity of models can be regularly audited. Only when the validity of models has been proven can these models be applied within the business.

As part of this procedure the product and process assumptions under which a model is valid need to be established. In addition, the uncertainty with which input parameters may be measured requires performance of a sensitivity analysis to determine the influence of key variables. In many cases only the effects of significant cost drivers, such as production volume, need to be investigated to reveal the boundaries of possible change.

2.6 Developing the Cost Estimating Relationships

2.6.1 Introduction

The primary functions of the data identification and data collection tasks are to assemble sufficient data from which the relationships between costs and the product and process features influencing costs can be derived. A variety of techniques have been employed to identify cost estimating relationships of which *regression analysis* and *parametric estimating* are amongst the most widely used of the traditional techniques.

Parametric estimating is essentially a top-down method of cost estimating (Mileham et al, 1993) but can be applied to more detailed costing applications (Apgar and Daschbach (1987). In this case, the top-down method means that a product or process cost is predicted from higher level resource descriptions. For example product costs are derived from product level specifications rather then detailed engineering designs of the individual components that make up the product. An advantage of this approach is that models may be generated at the time of estimation, e.g. at the concept design stage of product or process development, when more detailed information is not available. In this respect, Busch (1994) recommends a 'bottom-up' process based approach to the development of cost models for assisting in determining the commercial success of new technologies. This requires developing detailed process flowcharts for the new technologies. Whilst the methodology is appropriate to existing technologies that are in commercial use it is doubtful if sufficient detailed data would exist with respect to new technologies. Hence the methodology would be impractical in these situations both through lack of detailed process information but also through lack of data linking such information with the costs generated.

Although parametric estimating is normally identified as an individual estimating technique the cost model relationships employed are, in the main, derived using statistical regression techniques (Michaels and Wood, 1989; Cawthorne-Nugent et al, 1989, Ott, 1992). For the purposes of the current work, therefore, parametric estimating will be considered as a form of regression based model development.

2.6.2 Regression Analysis

There are a variety of regression based data analysis techniques available of which *multiple linear regression* is the commonest in use. This form of regression is basically an extension of the 'line of least squares method' (simple linear regression), and is a statistical technique used to establish the general relationship between a dependant variable and a number of independent variables (Crocker, 1967). Although a linear model is produced it can be used either when it expresses the exact functional relationship between a dependant variable and its predictor variables, or when it is an acceptably accurate approximation of a more complex relationship, e.g. a relationship known to be non-linear. Non-linear regression techniques are also available but dependent on the user pre-specifying the type of non-linear relationship that exists.

The advantage of using the regression technique to develop an estimating model is that if the model is assumed correct, it yields an unbiased and efficient estimate of the model's parameters with which to predict the value of the dependant variable given the values of the independent variables. However, because the regression technique cannot distinguish between a natural causal relationship between variables and one occurring by chance it is essential to choose the predictor variables with care. Therefore, it is important when selecting independent variables to use personnel who are familiar with the work to be estimated. This is achieved at present by consulting the relevant process experts and eliciting their opinions on which features generate cost. The use of a multi-skilled team for developing cost models is considered essential in this respect. Such a team needs to contain both product and process experts, cost engineers who understand the basic cost modelling process and personnel who understand the influence of environmental effects on costs.

Normally the list of predictor variables identified contain many that have little or no effect on costs. Hence this list needs to be refined in order to produce the final set of parameters with quantifiable cost relationships. The level of correlation for each of the possible parameters with cost needs to be established to enable a ranked set of process 'cost drivers' to be formulated. The level of correlation between individual variables can be calculated using single-parameter regression analysis.

When the refinement process has been completed, a set of parametric cost drivers, ranked in order according to their level of correlation, must be established. An arbitrary correlation cut-off level can then be applied to select the 'best' set of parameters from which effective cost-estimating equations can be derived.

When considering the increasing numbers of cost models that will be required to support future product and process development activities, this technique is becoming increasingly unable to support the cost model development needs, i.e.:

- **a.** there is normally a lack of significant cost examples when developing models for new materials and manufacturing processes, i.e. the available data may not be sufficient to obtain a valid cost relationship,

b. the technique can be sensitive to inconsistencies and irregularities in data, i.e. their accuracy depends strongly on the accuracy of the manufacturing data and manufacturing history on which they are based.

c. regression analysis quickly becomes ineffective as the number of predictor variables within a model increases, hence the technique may not cope with the increasing complexity of manufacturing processes,

d. use of the technique requires persons with expertise in both regression analysis and the manufacturing process being modelled,

e. accurately representing all the details of manufacturing complexity is difficult for a regression model as it must include all the product and process specific parameters which can influence the cost model, and

f. the expense of detailed cost data collection can be high and must be traded-off against the potential benefits.

2.6.3 Knowledge Based Systems

Rehman and Guenov (1998) present a method for modelling production costs throughout the design phase of a product's life cycle, i.e. from conceptual to detail design. The cost modelling methodology they use incorporates the use of knowledge-based and case-based approaches. The method developed is essentially a comparative estimating procedure in that the first step is to retrieve the closest matching past product case from a design case base. The new design is then simply a modification of the existing design and the computer-based system detects the design changes made. The cost data stored for the original component is then modified using expert opinion until a cost for the new component is arrived at.

Kingsman and de Souza (1997) developed a knowledge-based decision support system for cost estimation that was intended to replace the 'subjective judgement' cost estimators use when arriving at an estimated cost. It achieved this goal by making use of heuristic 'expert' rules to aid the estimating process and removed the bias and errors normally associated with the manual cost estimating process.

Chin and Wong (1996) have developed decision tables that contain technical data relating to the injection moulding process and details of the variables and their inter-relationships that influence costs during this process. Human experts have been used to derive a set of rules for extracting the relevant information from these tables that can then be used to derive a process cost. The method makes use of established cost relationships and, hence is not, in the true sense a cost modelling methodology merely a method of automating the cost estimation process. A similar methodology is the use of *cost tables* where Yoshikawa, Innes and Mitchell (1990) have noted that such tables have been used extensively by Japanese companies to estimate manufacturing costs of new processes prior to implementation. Dean (1989) used this concept to develop a multi-dimensional database in which cost is captured for individual attributes of the functions of a product. Should the attributes of a function be changed then these cost tables can be used to estimate the cost of the changes.

2.6.4 Feature Based Systems

Often a major constraint to the development of a concurrent engineering environment is the provision of costing systems that can generate costs from CAD inputs. In order to resolve this constraint many researchers have focused their efforts on the development of 'feature based' costing systems, including:

a. Hill, Forster and Smith (1994) in the area of detail and assembly within the aerospace industry,

b. Feng, Kusiak and Huang (1996) with respect to machining form features with cost relationships dependent on the type of form features and the relationship between form features,

c. Ou-Yang and Lin (1997) who developed a system for estimating manufacturing cost during the early product development stage, i.e. the system developed relied on cost information being available that could be accessed using the shape and precision of design features, and

d. Leibl, Hundal and Hoehne (1999) who developed a system for costing sheet metal components and assemblies which could be used at the concept stage of product design. Cost calculations were performed either using a database of costs or by comparison with existing component costs.

2.6.5 Computer-Aided Methods

In the past decade, the use of computers by industry has increased dramatically. The wide availability of personal computers, at reasonable prices, has encouraged many business applications previously requiring a mainframe. Cost estimating is one of those applications.

There are certain characteristics common among almost all computer-aided methods (Winchell, 1989). The first is that most computer-aided techniques make use of a knowledge base of the types described in Section 2.6.2. This database provides the essential information used to make cost calculations and hence may consist of formulas or information on existing production or prior estimates. Normally, it can be updated with new or revised information. The second commonality is that the computer-aided technique has provisions for calculating the costs by using information in the knowledge base combined with other data that may be input as the program is run. The third feature of cost estimating software is that it sums the costs in the required resource classifications such as direct labour, direct material and factory burden and formats outputs such that the information presented is useful to those who use it (Winchell, 1989).

There are a variety of computer-aided cost modelling systems available of which a typical example is that developed by Edwards and Wong (1987) who developed a simulation capable of estimating capital and operating costs for wood energy systems. The objectives guiding the design of the model were to:

- **a.** formalise a unit process building block approach for wood energy systems to facilitate analysis,
- **b.** embody in the model engineering knowledge that would assist those unfamiliar with wood energy systems, and

c. construct the model with design features that make it suitable for interactive use and future expansion and enhancement.

Previous work (Stockton and Wang, 1999) has indicated how several advanced modelling techniques, i.e. fuzzy logic and artificial neural networks, could potentially provide methods for successfully overcoming the constraints to the development of cost models (i.e. Table 1.3).

Chapter 3 Artificial Neural Networks

3.1 Background Theory

An initial developer of artificial neural networks was McCulloch and Pitts (1943) who outlined the first formal model for an elementary computing neuron. Further development of this concept occurred when Hebb (1949) identified how information could be stored in artificial neural network connections and proposed a learning scheme for updating a neuron's connection weights. A significant contribution to the development of artificial neural network technology was then made by Rosenblatt (1958) who developed the *perceptron*, i.e. hardware which, by training, can be made capable of learning such that it is possible to classify patterns by modifying connections to threshold elements.

During the 1950s, the first *neurocomputer* was built and tested (Minsky, 1954) but lacked sufficient computing power for the implementation of learning theorems capable of supporting complex computational problems. This lack of computing power resulted in artificial neural network research entering a stagnation phase until the mid-1970s when interest in the area revived leading to the development of:

a. advanced forms of artificial neural network architectures by Fukushima (1975, 1980) and Hopfield (1982, 1984)

b. novel forms of associative memory and unsupervised learning networks by Kohonen (1977, 1984, 1987),

c. the Adaptive Resonance Theory (ART) by Carpenter and Grossberg (1983, 1987, 1988, 1990),

d. a probabilistic artificial neural network model, (i.e. the Boltzmann Machine), by Hinton (1984, 1986).

An artificial neural network (Bode, 1998; De la Garza and Rouhana, 1995; Shtub and Zimerman, 1993; Bode. Ren and Shi, 1995b) consists of a number of computer *processing elements* of the type shown in Figure 3.1.

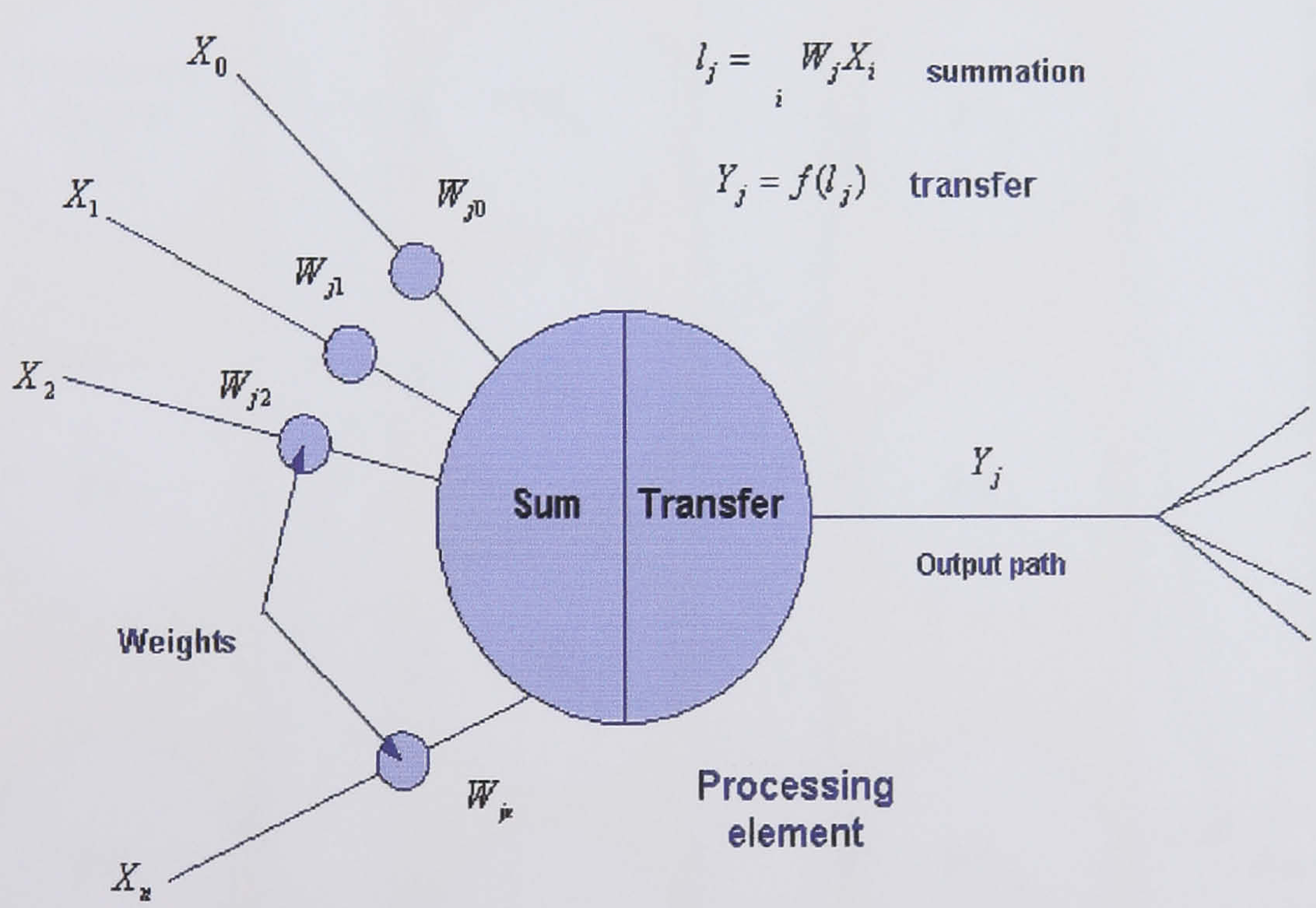

Figure 3.1 Artificial Neural Network Processing Element

These *processing elements* are arranged in layers (Wang and Stockton, 1999), as illustrated in Figure 3.2, such that they represent a mathematical model of the physical processes that take place in brain cells. In an artificial neural network a *processing element* (PE) has many input paths and combines, normally by a simple summation, the values of these input paths. The combined input within a *processing element* is then modified by a transfer function. This transfer function can either be:

a. a threshold function, which passes information only if the combined activity level reaches a certain level, or

b. a continuous function of the combined input.

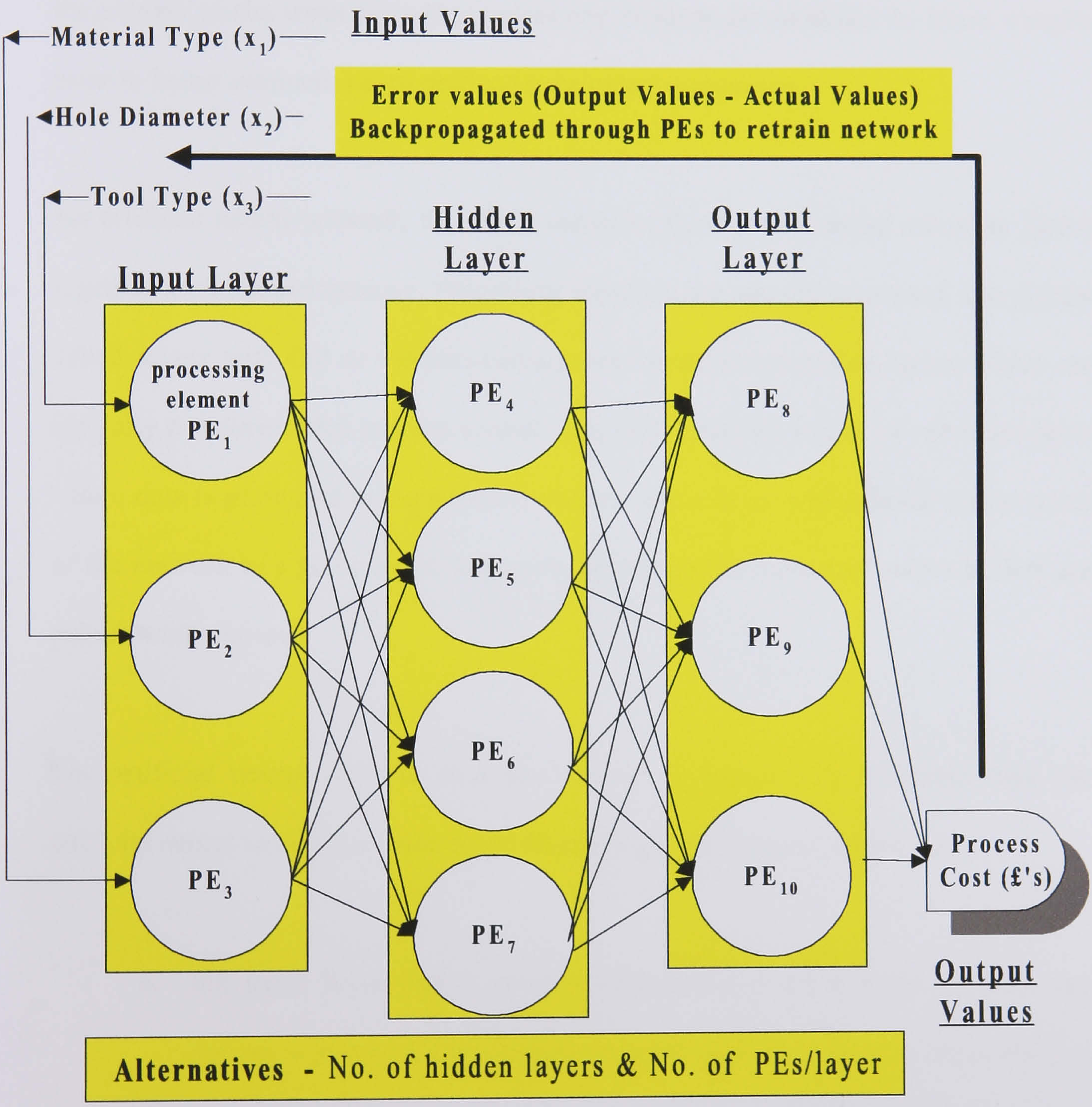

Figure 3.2 Artificial Neural Network Structure

The values output from transfer functions are generally passed directly to the output paths of processing elements. These paths can be connected to input paths of other processing elements through connection weights, which correspond to the synaptic strength of the neural connections. Since each connection has a corresponding weight, the signals on the input lines to a processing element are modified by these weights prior to being summed, i.e. to produce a weighted summation.

An artificial neural network, therefore, consists of many processing elements joined together in the above manner. Processing elements are usually organised into groups called *layers* with full or random connections between successive layers. There are typically *two layers* that possess connections to the outside world, i.e. an *input layer* where data is presented to the network, and an *output layer* which holds the response of the network to a given input. Layers distinct from the input and output buffers are called *hidden layers*.

The artificial neural network structure (shown in Figure 3.2) illustrates how the artificial neural network is made up of these three basic types of layers, i.e.

- **a.** the input layer which accepts information from external sources and assigns weighted values to these depending on their relative importance as cost drivers,
- **b.** the hidden layer which processes this input information and converts it to the required output data, and
- **c.** the output layer which outputs cost data from the artificial neural network.

The number of processing elements contained in a layer can be varied as can the number of hidden layers within any individual network. Processing elements within layers are normally "fully connected," i.e. an individual processing element within a layer is connected to all processing elements in both the preceding and succeeding layers. Processing elements within the same layer are, however, not connected.

As values for process variables are input into the artificial neural network, the processing elements within the input, hidden and output layers are modified such that the difference between the output cost values and actual cost values, i.e. the error, is gradually minimised. This process, termed ' training the network' is performed within the current research work using 'back-propagation', i.e. this technique calculates an error between actual values and output values and propagates the error information back through the network to each node, (i.e. processing element), in each layer. This back-propagated error then drives the learning at each node. Learning is, therefore, the process of adapting or modifying the connection weights in response to stimuli being presented at the input buffer and optionally at the output buffer. The basic types of learning processes within artificial neural networks are:

- **a.** *supervised learning* in which the stimulus provided at the output layer corresponds to a desired response to a given input provided by a knowledgeable teacher,
- **b.** *unsupervised learning* in which no desired output is shown, and
- **c.** *reinforcement learning* where the learning an external teacher indicates only whether the response to an input is good or bad.

Each of the above learning mechanisms requires application of a *learning rule,* which specifies how weights adapt in response to a learning example. For example, learning may require showing a network many examples, many thousands of times, or only once. The parameters governing a learning rule may change over time as the network progresses through its learning phase.

Once the learning process is complete, the next phase in the operation of an artificial neural network is *recall,* which refers to how the network processes a stimulus presented at its input buffer and from this input creates a response at the output buffer. Often a recall is an integral part of the learning process. This is particularly true when, in order to create an error signal, a desired response of the network must be compared to the actual output of the network.

The simplest form of a network has no feedback connections from one layer to another or to itself. Such a network is called a "feedforward network". In this case, information is passed from the input buffer, through intermediate layers to the output layer, using the summation and transfer function characteristics of the particular network.

Operations used within artificial neural networks that affect entire layers are *normalisation* and *competition*. The former operation, takes the value that corresponds to the output of a complete layer, and scales it such that the total output is a fixed value. These connections allow the processing elements to individually sense the total layer output and adjust their own values accordingly. The result of normalisation is that the total activity in the layer remains approximately constant. The latter operation, *competition*, refers to the interaction a processing element may have with each other processing element in the same layer. Unlike normalisation, where all processing elements adjust their output to create a fixed level of activity, in competition, only one or a few processing elements win, and, therefore, produce an output. A common form of competition occurs when the processing element with the highest activity is the only unit within its level to output its current state.

3.2 Applications of Artificial Neural Networks

Recently, artificial neural networks have generated much research interest in the manufacturing area although many of the applications reported in the literature are either laboratory experiments or preliminary applications. Primary areas of application have been monitoring and diagnosis (Gövekar, Grabec and Peklenik, 1989), process modelling and control (Gingrich, Kuespert and McAvoy, 1992), engineering design (Venugopal and Narendran, 1992), process planning (Knapp and Wang, 1992), and group technology (Kamal and Burke, 1996, Kaparthi and Suresh, 1991). This latter application involved identifying component families and the allocation of these families to suitable manufacturing cells. A variety of optimisation problems (Sette et al, 1996) have also been examined using back propagation methods and, Hopfield and ART networks.

Lippmann, (1987) identified several potential advantages, when compared to conventional methods, of using artificial neural networks, i.e.:

a. they require less assumptions to be made concerning the shapes of underlying distributions than traditional statistical methods and may thus prove to be more robust when distributions are strongly non-Gaussian,

b. they can easily run on parallel processors due to the inherent parallelism of their architecture, hence computing time is shortened, and

c. they provide a high degree of robustness or fault tolerance because they are composed of many processing nodes, and hence damage to a few nodes or links need not significantly impair the overall performance.

Several years later Udo (1992) provided a further review of artificial neural network applications within manufacturing processes, i.e. the primary areas identified at this time were:

a) resource allocation and constraints satisfaction,
b) scheduling and allocation of maintenance resources,
c) process control and planning,
d) management of databases,
e) control of robots, and
f) quality control and machine vision

3.2.1 Applications of Artificial Neural Networks in Cost Estimation

Early attempts to embed artificial neural networks techniques within the cost estimation area include Shtub and Zimerman (1993) who developed models for estimating the cost of assembly systems, and Ehrlenspiel and Schaal (1992) and

Becker and Prischmann (1993) who developed cost models using curve-fitting multi-layer networks. Performance evaluation and a systematic comparison with conventional methods were not undertaken during this work.

König (1995), when developing models for costing the injection moulding of telephone housings, compared the estimation quality of artificial neural networks with that of conventional linear and non-linear regression analysis. In general, artificial neural networks estimated costs with higher levels of accuracy than conventional methods. However, the results were based on a small number of testing data and thus could be prone to statistical errors. In common with conventional statistical methods, particularly regression analysis, Haykin (1994) identified essential characteristics of ANNs that indicated their validity as cost modelling techniques, i.e. the ability to learn, ease of adapting to a variety of costing situations, and ability to model non-linear relationships.

Further work included Bode et al. (1995a, 1995b, 1995c), Bode and Ren (1996) and Zhang, Fuh and Chan (1996) who demonstrated the potential of using artificial neural networks to develop a model capable of representing the relationship between product cost and cost-related features of packaging products. They adopted, after a 'trial and error' process a back-propagated artificial neural network that used supervised learning to train the network. Again 'trial and error' methods were used to determine the number of hidden layers and neurons in each hidden layer. It is interesting to note that to overcome the lack of substantial amounts of cost data with which to train the network the researchers selected 40 samples at random but used these 8000 times to train the network.

Smith and Mason (1997) compared the use of regression and ANN methods of developing cost estimating models. They used the *design of experiments* methodology to test the effect of four factors, i.e. the modelling method of developing cost estimating relationships (CER), sample size available for CER construction, magnitude and distribution of data imperfections (noise) and the bias of the sampled data. For each CER Method, a full factorial experiment with five levels of construction sample size, three levels of noise and three levels of bias was created resulting in a total of 45 separate prediction models for each CER. The performance indicated that the best case would be a large sample size with perfect sampling and perfect adherence to the CER; the worst case would be the smallest sample with biased sampling and significant noise in the relationship between x and y and z.

Lee, Cheng and Balakrishnan (1998) developed an artificial neural network based model for estimating the costs of developing computer software packages. Their main concerns were to provide cost models capable of providing cost data during the early phases of the software development life cycle. Their work initially used cluster analysis to group together similar software development projects in order to provide data for training the network. This approach although improving the training efficiency of the networks developed restricted the range over which each cost model could be considered valid.

Bode (1998) used artificial neural networks to estimate the total cost of single-groove ball bearings. Although based on a simple principle, bearings differ considerably in geometry, material, and design. Hence the ANN had to successfully deal with a wide range of variety in terms of:

a) outer diameter ranges, i.e. from 9mm to 260mm,

b) width ranges from 2.5mm to 55mm,

c) differing material types,

d) a range of design combinations, and

e) output cost ranges from 6 cost units up to 1,000 cost units.

Shtub and Versano (1999) compared the efficiency of using artificial neural networks with that of regression analysis when developing models for estimating the cost of bending steel pipes. Again a number of ANN based models were needed to estimate the cost of repetitive operations in a typical manufacturing environment such that design to cost environments could be supported.

Bode (2000) has concluded that artificial neural networks produce better cost predictions than conventional costing methods only if a number of conditions hold (Bode, 2000), i.e.:

i. a sufficient cost case base is available, i.e. the use of ANN modelling techniques generally requires a substantial body of known cost cases for training. This requirement poses problems when developing models for costing during the new product development process since this process normally deals with novelty and thus past cost cases are usually scarce.

ii. cost-driving attributes are known prior to the start of modelling, i.e. artificial neural networks, as with other cost estimation methods derive costs from known attribute values. Identifying cost drivers normally requires a high level of product and process expertise.

3.3 Artificial Neural Network Processing Elements

The processing element forms the heart of the artificial neural network and it is the functions associated with these elements that provide the artificial neural network with the ability to model a wide variety of relationships between input and output variables. Figure 3.3 illustrates the structure of a typical processing element used within the current research work.

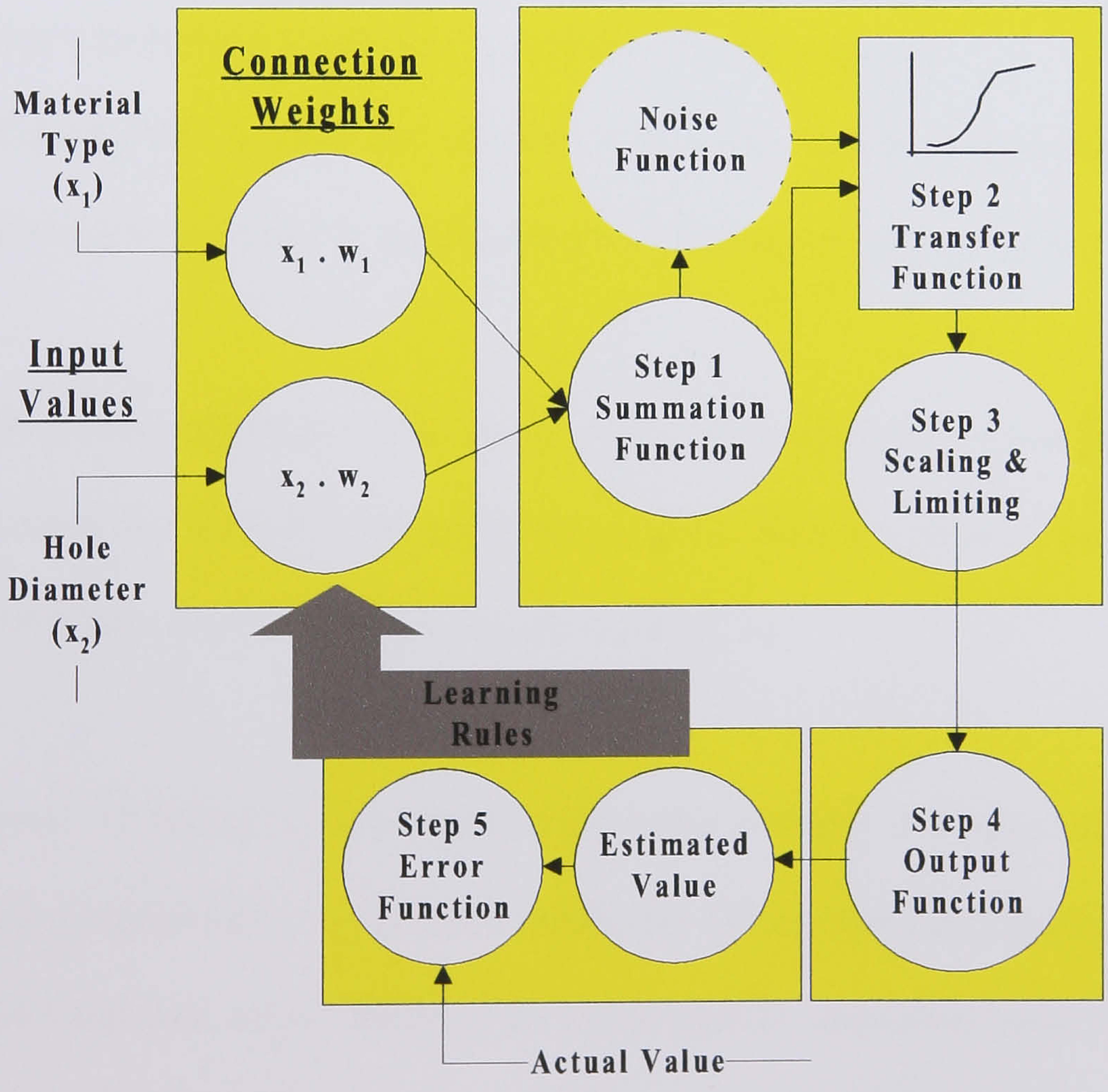

Figure 3.3 Function of Processing Element

Processing elements (PEs) (NeuralWare Inc., 1996) contain a number of mathematical functions as shown in Figure 3.3. These functions act in a sequential manner to transform input values into output values. Input values can either be externally derived input values of predictor variables or outputs from processing elements in a preceding layer. The functional steps within this sequence are as follows:

Step 1: Weighted Summation Function - Weightings are applied to each of the variable values input into a PE and the summation function then sums these weighted variable values. Two methods of summing the weighted inputs have been examined in the current research, i.e.:

i) **Sum** which is the traditional sum of the effective inputs.
ii) **Majority** that counts the number of effective inputs greater than zero and subtracts the number of effective inputs less than or equal to zero.

Step 2: Transfer Function - The result of the weighted sum is transformed to a working output or "transfer " output by the transfer function. Four types of transfer function have been examined in the current research, i.e.:

i) **Linear Function** in which the transfer value is simply the input value.
ii) **Sigmoid Function**, which maps inputs into values between 0 and 1.
iii) **Sine Function**, which transfers the trigonometric sine of the input value.
iv) **TanH (Hyperbolic Tangent)**, similar to the sigmoid function, but maps input values into the range -1 to $+1$.

Prior to applying the transfer function, uniformly distributed random noise may be added. Three types of noise function have been examined in the current research, i.e.:

i) **Uniform Noise** in which a random value is applied to each PE in a layer.

ii) **Gaussian Noise** where again a random value is applied to PE's, however these random values are normally distributed.

iii) **No Noise**, i.e. no noise function is applied.

Step 3: Scaling and Limiting - Scaling is used to perform a linear transformation on the result of the transfer function. After scaling is applied, transfer function is cliped to the upper and lower limits.

Step 4: Output Function - This provides a method of allowing processing elements within a layer to compete with each other. Competition can occur to determine which PEs provide outputs to PEs in succeeding layers and/or to determine which PEs will participate in the learning or adaptation process. Three methods of determining the participation of PEs have been examined in the current research, i.e.:

i) **Direct** in which there is no competition between PEs.

ii) **Select** in which if a PE has "learned", then the output value for a single PE is set equal to the current transfer value for a single PE. If a PE has never "learned", the output value for a single PE is set equal to zero.

iii) **One-Highest** in which processing elements when they compete for output, only the first winner will learn or adapt and no other processing elements in the layer will adapt its weight.

Step 5: Error Function - Three methods have been examined in the current research for transforming the raw error, i.e. the difference between the current output and the desired output. These methods are:

i) **Standard** function in which no transformation takes place.

ii) **Quadratic** function in which the error is squared but retains its sign.

iii) **Cubic** function which cubes the error.

The latter two functions increase the importance of large errors. A scale is then applied to the resulting error function in order to either increase or decrease the error associated with a particular PE. The resulting value is termed the 'current error'.

Step 6: Back-Propagation - The process of back-propagation consists of multiplying connection weights by a specific value and then adding the resulting value to the error field in the source processing element. Depending on the network type the back-propagated value is either the current error, the current error scaled by the derivative of the transfer function or the desired output.

Step 7: Learning Rules - Variable connection weights are modified according to a learning rule of which four have been examined, i.e. the following learning rules have been compared in the current research, i.e.:

i) **Hebb Rule** where if both the desired output and the input are above a threshold value then the connecting weight is incremented by a set learning rate.

ii) **Perceptron Rule** it uses a derived amount to change the connection weights between processing elements. Individual weight changes depend on actual and desired output values of processing elements. A simple rule is used to determine if weight changes should be applied, i.e. if the output from an individual PE is active and is intended to be active, then do not apply the weight changes, otherwise apply the weight changes.

iii) **Delta Rule** in which the error between the desired output and the actual output transformed by the derivative of the transfer function, is "back-propagated" to prior layers until the first layer is reached.

iv) **Ext DBD Rule** where if the error is less than the previous minimum error, the weights are saved in memory as the current best. But if the current error exceeds the minimum previous error, all connection weight values revert stochastically to the stored best set of weights in memory and in addition, the learning rate and momentum rate are decreased to begin recovery.

If some form of competition for learning is in effect, only the weights belonging to the "winning" processing element will be updated. Learning rules will use one or more of the learning coefficients from the learning and recall schedule. These coefficients will have different meanings depending on the particular learning rule.

3.4 Influence of ANN Structure

A central theme highlighted by the research literature is that of the difficulties involved in the selection of the most appropriate network structure for individual modelling applications, for example:

a. Kamarthi et al (1990) developed a two-layer artificial neural network for grouping parts during Group Technology exercises. At this time they reported the need to study different artificial neural network structures suitable for storing, retrieving and classifying components based on their design and manufacturing attributes.

b. Udo (1992) provided an overview of artificial neural network applications within manufacturing processes and identified the need for the development of a generalised network for solving different types of problems. The problem of how artificial neural network structures can be generalised was also identified by Looi (1992) when investigating the use of artificial neural network methods in combinatorial optimisation problems.

c. Arizono et al (1992) used artificial neural networks as a method for developing schedules that minimised total actual flow times. They concluded that if an appropriate network could be defined then these techniques could offer potential methods of solving a range of scheduling problem types. They identified that a significant problem was the question of reasonably specifying the values of parameters and weights included in the network model.

d. Rao et al (1993) constructed several artificial neural networks, using a hybrid neural-experts systems approach, i.e. they developed one network model for each cost item that needed to be output since they found that:

i. The final quality of a network depends both on the structure of its layers and the method by which data is presented to the network during training. Hence they used the expert system to manage data inputs to the network

ii. The number of output neurons should be significantly less than the number of input neurons for a network to learn effectively

e. Li et al (1994) developed artificial neural network models for the selection of grinding wheels by using data obtained from manufacturers specification handbooks to train the network. Prime difficulties faced were the selection of the optimal number of neurons in the hidden layer. With the absence of a formal methodology their way of dealing with the problem was to start with a small number of hidden neurons and then gradually increase the number of neurons in the hidden layer until an acceptable accuracy was obtained.

f. Luong and Spedding (1995) developed a back-propagation artificial neural network for predicting, from selected machining conditions, the cutting forces and surface finish that would result. During their work a single network was to be developed. However, this network failed to converge during training. Hence they chose a set of sub-networks. They identified that no unified or formulated procedures existed for designing appropriate networks and concluded that network design is still very much a black art. They identified the questions to be answered when developing such a system, i.e.:

a) selection of the network type,

b) number of layers including hidden layers,

c) number of processing elements in each layer, and

d) type of transfer function.

Additional factors that have been found to influence the effectiveness of an ANN and where decisions are often taken based on trial and error include:

a) the network topology,

b) the network parameters such as learning rate and momentum factor,

c) the maximum and minimum value of weights,

d) the number of examples in a training set,

e) whether the nature of the examples in a training set encompasses the diversity of a problem,

f) the extent to which the examples are learned, and

g) the type of learning method used.

In the main only general statements concerning the selection of ANN structural elements are provided by the research literature. For example, according to Geman et al. (1992) the normal understanding is that the generalisation ability of a network will increase as the number of hidden nodes increases. In addition, networks may not learn properly if there are too few hidden nodes, whereas too many nodes would generate redundant nodes to deteriorate the performance of the network. Over-training is also reputed to reduce the 'generalisation' ability of a network (Martinez et al., 1994).

3.5 Potential Benefits and Limitations When Using Artificial Neural Networks

With reference to the individual characteristics of cost models, (i.e. Figure 3.2), the artificial neural network (ANN) approaches to the development of cost models may offer advantages over the use of traditional techniques, i.e.:

3.5.1 Range of Application Areas

ANNs are able to learn any complex non-linear mapping of a continuous function. Hence, there is potentially no limit to the type and variety of tasks that can be costed using the ANN approaches since the methods are not problem-type dependent. ANNs have added advantages since they are applicable to problems which are difficult to structure for solution purposes, e.g. situations in which several items of equipment may share specific cost resources. The potential also exists for linking individual ANNs such that they perform a sequence of tasks, e.g. an initial ANN grouping cost types according to similar criteria and subsequent ANNs developing individual cost models for individual groups.

3.5.2 Estimating Accuracy

Published research into costing applications of ANNs report increases in estimating accuracy over the use of regression analysis. However, with respect to the artificial neural network, the achievable accuracy is dependent on effective selection of the various elements, (i.e. Figures 3.2 and 3.3), that make up such systems.

There are no reported limitations on the form of the cost function that can be identified using artificial neural networks, i.e. both linear and non-linear functions can be accommodated. In this respect ANNs can assign different function forms to individual variables within the network. For example, within the same artificial neural network, drilling costs may be linearly related to hole length but possess a non-linear relationship with hole diameter.

Confidence in the validity of models developed using parametric methods is a recognised problem regardless of what parametric technique is used. However, when using regression analysis, this problem is partly offset since the resulting model can normally be checked for validity using the practical experience of users. A model developed using ANNs will not have this advantage since it will bear no relationship with normal parametric models. To the user the model is merely a collection of weights, network architecture and nodal transfer functions. In order, therefore, to maintain confidence in such a model it is necessary to ensure that its use is frequently audited and at regular intervals the model is updated using actual cost data. In this respect, this problem is partly offset since artificial neural network models can be easily updated.

3.5.3 User Personnel

Prior to using ANNs it is not normally necessary to make any assumptions concerning the form of the cost function under study, i.e. ANNs may not require pre-determination of the cost function type. In addition, the development of artificial neural network models can be highly automated again minimising human involvement. Potentially, these are important advantages over the use of regression analysis since they could significantly reduce the level of expertise required by users in the cost application areas under examination.

In general there is a significant lack of guidance available, within the costing area, on ANN network selection and design. Because cost application areas can be radically different, therefore, users may need the requisite expertise to perform empirical studies to ensure that an effective artificial neural network is established. In this respect areas of importance for establishing an effective artificial neural network include:

- **a.** the selection of the data to be used for training the network,
- **b.** the order in which data is presented during training,
- **c.** the selection of data for testing the network, and
- **d.** developing the optimum network configuration parameters, i.e. in terms of number of hidden layers, number of processing elements in each layer and choice of transfer functions.

3.5.4 Set-Up and Operating Costs

In order to develop an ANN based cost model it is necessary to purchase appropriate software development tools and to train the intended users. This software can then be used to develop cost models over a wide range of application areas. With respect to ANNs, a large amount of time may be required to design the network architecture and correctly set, for a specific cost application, the parameters for the weights and transfer functions. There have been instances recorded in which networks have failed to be trained, hence necessitating re-examination of the data set and where necessary repeating network development tasks.

3.5.5 Data Requirements

Artificial neural networks, have the ability to differentiate between the relative importance of predictor variables and hence establish which are the cost drivers. This selection process does, however, pre-suppose that cost examples containing the important cost drivers have been collected and used to train the network. Artificial neural networks also have the ability to make use of predictor variables with only an indirect relationship to the actual costs being estimated. Also ANNs are flexible with respect to incomplete, missing and noisy data, i.e. ANNs are "fault tolerant".

Chapter 4 Experimental Design

4.1 Introduction

Chapter 3 identified the essential structure of an ANN which consists of input, hidden and output layers containing one or more processing elements. The literature reviewed indicated that not only does the number of hidden layers affect the performance of an ANN but also the number of processing elements per layer and the characteristics of the individual processing elements. The ANN methodology can, therefore, only be considered a prototype cost modelling technique and any ANN structure chosen at random may be functional but it may be far from optimum in terms of the quality of its outputs and the cost of generating these outputs.

It is, therefore, necessary to identify a 'robust' artificial neural network structure, i.e. the selection of the most appropriate structural elements that would provide acceptable estimating accuracy over a wide range of costing application areas. This requires a series of experiments to be conducted to identify the most appropriate settings of the ANN structural elements.

In order to perform appropriate experimentation it was necessary to select suitable cost modelling application areas. In this respect the areas chosen were *turning* and *drilling.*

An artificial neural network package software, i.e. NeuralWorks Pro. II/ PLUS (NeuralWare, Inc. 1990), has been used to develop the required networks. It is a C-based simulator that provides a system for choosing individual PE function types and therefore for developing individual artificial neural network models.

4.2 Costing Application Areas

4.2.1 Turning Cost Model

With respect to the *turning* application area the model chosen was that published by Boothroyd and Reynolds (1989). A spreadsheet-based version of this model was created and used to generate the costing information that trained and tested the ANN cost models. Smith and Mason (1997) adopted this method of generating costing examples since it provided the advantage of knowing, for certain, what the true underlying relationships are between predictor variables and costs. Hence, the performance of an ANN in predicting these relationships could be measured with a high level of certainty. In addition, this model was chosen as suitable for use within the experimentation since it contained a relatively large number of predictor variables, i.e. 16), and both linear and non-linear relationships between these variables and process costs.

Turning is the machining operation that produces cylindrical parts. In its basic form, it can be defined as the machining of an external surface with:

a. the workpiece rotating,

b. a single-point cutting tool, and

c. the cutting tool feeding parallel to the axis of the work piece and at a distance that will remove the outer surface of the work.

The model developed by Boothroyd and Reynolds (1989) can be broken down into the following major elements, i.e.

i. Machining time for roughing operations, t_{mp}, (secs) assuming that maximum power is used is given by:

$$t_{mp} = \frac{60 r_v p_s W}{d_m a W^b} = \left(\frac{60 r_v p_s}{d_m a}\right) W^{(1-b)} \qquad (1)$$

Where:

r_v = proportion of the initial volume

P_s = specific cutting energy or unit power for the work material (hp. min/in^3)

W = weight of the work piece (lb)

d_m = density of the work material (lb/in^3)

a = constants

b = constants

ii. Non-productive time, t_{np} (secs)is given by:

$$t_{np} = (t_{sa} + n_t t_{sb}) / B_S + t_{\ln} + n_o t_{pt} \qquad (2)$$

Where:

t_{sa} = basic set-up time for machine

n_t = number of tools

t_{sb} = set-up time per tool

B_s = batch size

$t_{\ln}$ = loading and unloading time

n_0 = number of operations

t_{pt} = tool positioning time per operation

iii. Finish machining time, t_{mc} (secs), will then be given by:

$$t_{mc} = \frac{60A}{R_{sg}} s \tag{3}$$

Where:

A = effective area to be machined

R_{sg} = a machinability factor

iv. Effective area to be machined, A, assuming that all surfaces on the work piece are to be finished, including a through bore, is given approximately by:

$$A = 3.7\left(\frac{1-r_i}{2l_r} + 1 + r_i^{0.5} - \frac{r_e}{1.5}\right)l_r^{0.33} \frac{W^{0.67}}{d_m^{0.67}} \tag{4}$$

Where:

r_i = proportion of material removed by internal machining

r_e = proportion of material removed by external machining

l_r = length/diameter ratio of the work piece

v. Worn tool replacement costs can be significant when operating under optimum (minimum cost) conditions. It has been shown that these costs can be allowed for by modifying Equation (3) as follows:

$$t'_{mc} = \frac{60A}{R_{sg}}(\frac{1}{1-n}) \tag{5}$$

Where:

n = taylor tool life index

vi. When machining is carried out at maximum power, the corrected value of t_{mp} (secs) to allow for tool replacement costs is:

$$t'_{mp} = t_{mp}\{1 + (\frac{1}{1-n})(\frac{t_{mc}}{t_{mp}})^{1/n}\}s \tag{6}$$

When $t_{mc} / t_{mp} < 1$, this correction, however, will be small unless the maximum power conditions are close to the recommended conditions, which will not usually be the case for finishing operations.

An analysis of the relationships between each of the above variables and process costs is shown in Table 4.1 in terms of whether they represent linear and/or non-linear types.

Variables	Linear Relationship	Non Linear Relationship	Both Types of Relationship
n			√
r_v			√
P_s			√
W		√	
d_m			√
R_{sg}		√	
r_i		√	
r_e		√	
l_r		√	
t_{sa}	√		
n_t	√		
t_{sb}	√		
B_s		√	
t_{In}	√		
n_0	√		
t_{pt}	√		

Table 4.1 Relationships Between Variables and Process Costs

Tables 4.2 and 4.3 provide an analysis that indicates the time, effort and resources required, in practice, to collect data from which an ANN model could be developed. It has been identified in Chapter 2 that these factors must be taken into consideration when determining the effectiveness of any cost modelling methodology.

Variables	Empirical Data from Reference Books	Data Gathered from Company Data Sheets and In-House Knowledge	Data Inferred from Generic Models
$\boldsymbol{n}$	√		
r_v		√	
P_s	√		
W		√	
d_m	√		
R_{sg}	√		
r_i		√	
r_e		√	
l_r	√		
t_{sa}			√
n_t	√		
t_{sb}			√
B_s	√		
t_{ln}			√
n_0		√	
t_{pt}			√

Table 4.2 Data Sources

Variables	Level of Detail Input Data Required	Who Would Collect Data	Data Collection Method	Cost of Data Collection	Time Required to Collect Input Data
n	High	Manufacturing Engineers	Reference Books	Low	Short
r_v	Medium	Shopfloor Technician	Time Study/Video Recording	High	Very Long
P_s	High	Manufacturing Engineers	Reference Books	Low	Short
W	High	Manufacturing Engineers	Reference Books	Low	Short
d_m	High	Manufacturing Engineers	Reference Books	Low	Short
R_{sg}	High	Manufacturing Engineers	Reference Books	Medium	Long
r_i	Medium	Shopfloor Technicians	Time Study/Video Recording	High	Very Long
r_e	Medium	Shopfloor Technicians	Time Study/Video Recording	High	Very Long
l_r	High	Manufacturing Engineers	Reference Books	Medium	Short
t_{sa}	Low	Shopfloor Technicians	Time Study/Video Recording	High	Very Long
n_t	High	Shopfloor Technician	Reference Books	Low	Short
t_{sb}	Low	Shopfloor Technician	Time Study/Video Recording	High	Very Long
B_s	High	Manufacturing Engineers	Production Studies	Medium	Long
$t_{\ln}$	Low	Shopfloor Technician	Time Study/Video Recording	High	Very Long
n_0	High	Shopfloor Technician	Production Studies	Medium	Long
t_{pt}	Low	Shopfloor Technician	Time Study/Video Recording	High	Very Long

Table 4.3 Data Collection Analysis

4.2.2 Drilling Cost Model

In terms of the *drilling* application area process time data obtained from aerospace assembly operations was chosen. In this respect, within the manufacturing industry, the labour costs associated with the drilling process can represent for some products a significant amount of the overall manufacturing and assembly time.

The precise form of the model was not known and the process time data collected reflected the effect of many of the qualitative variables that influence such times. That is, although the drilling process itself appears relatively simple, the number and variety of variables involved cause considerable difficulty when attempting to estimate process times. This is particularly true when pre-drilling, (e.g. component loading), and post drilling, (e.g. component unload, tool changing), operations need to be considered.

The variety of factors that influence the drilling process time, include:

a. part material,

b. machine type,

c. drill type,

d. drill material,

e. hole thickness,

f. hole diameter,

g. speed and feed rate, and

h. tool tip type.

In addition, within certain industries such as aerospace manufacture, there are many other constraints that can have significant effects on the overall process time, including:

a. accessibility of the hole to be drilled,
b. multi-layer holes in which each layer consists of a different material,
c. tolerance and positional accuracy, and
d. swarf generation causing damage to softer materials.

The variables used to develop and compare alternative ANN models are listed below, the range of variables are those used in practice by industry collaborators.

a. Thickness of hole being drilled, **Th**, i.e. thicknesses ranged from 2.5mm to 25.4mm,
b. Speed of drill, **SR**, i.e. speed rate was varied from 180 revs/min to 550 revs/min,
c. Hole diameter, **HD**, i.e. diameter was varied from 6.35mm to 25.4mm, and
d. Number of layers, **NL,** i.e. aluminium, titanium, 3-layer component consisting of aluminium top layer, titanium middle layer, aluminium bottom layer.

Table 4.4 provides a sample of the data used to generate estimating models using the artificial neural network procedures.

Data Samples	Th	SR	HD	NL	Drilling Time (Secs)
1	2.5	550	6.35	1	9
2	4	550	6.35	1	25
3	10	550	6.35	1	50
4	11.5	360	12.7	1	11
5	16	360	12.7	1	33
6	25.4	360	12.7	1	79
7	5	360	17.5	1	17
8	10	360	17.5	1	46
9	17	360	17.5	1	120
10	9	180	25.4	1	22
11	10	180	25.4	1	78
12	17	180	25.4	1	193
13	18	550	6.35	3	15
14	10	550	6.35	3	37
15	19	550	6.35	3	83
16	4	360	12.7	3	18
17	10	360	12.7	3	49
18	25.4	360	12.7	3	112
19	5	180	17.5	3	26
20	19	180	17.5	3	82
21	18	180	17.5	3	197
22	12.7	550	6.35	1	11
23	10	550	6.35	1	33
24	25.4	550	6.35	1	79
25	19	360	12.7	1	14
26	18	360	12.7	1	45
27	4	360	12.7	1	108
28	2.5	180	17.5	1	22

Table 4.4 Sample of Drilling Data Used

4.3 Experiments to Identify Optimum ANN Structural Elements

Experimenting with the ANN structural elements one at a time, i.e. a "full factorial" approach, or by trial and error until a first feasible design is found, is one approach to identifying optimum artificial neural network structures [Bendell, 1988; Phadke, 1989]. However, this approach results in a long and costly time span for completing the experimentation, And hence the likelihood of premature termination of the experimental process due to budget and/or time pressures. In these circumstances the result could have been an ANN structure far from optimal. As an example, if 13 ANN parameters at 3 levels are to be studied, varying one factor at a time would require studying 1,594,323 experimental configurations (3^{13}).

An alternative approach, that was adopted for the current research, is provided by the Taguchi Methodology which was developed by Genichi Taguchi (1987), in order to provide suitable techniques for improving the implementation of total quality control within Japanese manufacturing organisations. Taguchi methods (Taguchi and Yokoyama (1994), Peace (1993), Fowlkes and Creveling (1995), Song, Mathur, and Pattipati (1995)) are claimed to have provided as much as 80% of Japanese quality gains which according to Dertouzos, Lester, and Solow (1989) has been responsible for a severe decline in the industrial competitiveness of many USA organisations.

Taguchi's Methodology, often termed the 'robust design method' provides the designer with a systematic and efficient approach for conducting experimentation to determine near optimum settings of design parameters for performance and cost (Bendell, 1988; Kackar, 1985; Logothetis and Salmon, 1988; Meisl, 1990; Phadke, 1989). Robust design has been used successfully in Japan in designing reliable, high quality products at low cost in such areas as automobiles and consumer electronics (Cullen and Hollingum, 1987; Logothetis and Salmon, 1988; Sullivan, 1987; Phadke, 1989; Wille, 1990). The approach is equally applicable to the optimisation of a wide variety of quality characteristics such as weight, processing time, yield, structural strength and surface defects. Bryne and Taguchi (1986); Phadke (1989); Taguchi (1986); Logothetis and Salmon (1988) and Wille (1990) provide numerous applications for optimising single or multiple quality characteristics.

The mathematical tools that form the methodology are primarily based on the statistical theory underpinning the concepts of 'design of experiments' (Gunter, 1987; Phadke, 1989; Wille, 1990). Essentially the Taguchi Methodology enables a series of experiments to be designed that will enable identification of the optimal quality characteristics for a specific objective. In terms of product and process design, therefore, the methodology provides a systematic approach for determining the optimum configuration of design parameters for performance, quality and cost.

The basis of the Taguchi methodology is the use of orthogonal arrays (OA) that are used to select a range of experiments capable of efficiently studying parameter spaces that contain a large number of decision variables. Orthogonal arrays, first developed in the 1930s by R.A. Fisher and L.H.C. Tippett in England (Fisher, 1925; Tippett, 1934), enable the number of experiments to be significantly reduced. Taguchi has considerably simplified the use of orthogonal arrays by providing tabulated sets of standard orthogonal arrays (American Supplier Institute Inc, 1989; Bendell, 1988; Phadke, 1989). The choice of an OA (Ross, 1988) depends on the number of degrees of freedom required for studying the main and interaction effects.

An example of a typical orthogonal array is illustrated in Table 4.5. In this array, the columns are mutually orthogonal, i.e. for any pair of columns, all combinations of factor levels occur an equal number of times. Table 4.5 illustrates an 'L9' design where there are four factors, A, B, C, and D, each at three levels, 1, 2 and 3. The '9' indicates the number of rows, i.e. the number of configurations to be tested, with test characteristics defined by the row of the table.

Experiment Numbers	Factors			
	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 4.5 L9 (3^4) Orthogonal Array

The number of columns of an OA represents the maximum number of factors that can be studied using that array. Note that this design reduces 81 (3^4) configurations to 9.

In summary the primary benefits of using the Taguchi Methodology are:

a) simplicity of implementation., i.e. they are often applied, by technicians, on the manufacturing floor to improve product and/or processes, and

b) minimisation of the number of experiments necessary to obtain the answer to a problem, hence minimisation of effort and cost.

4.4 Application of Taguchi Methodology

The main function of an ANN based cost modelling tool is to generate cost estimates that are accurate and inexpensive to generate in terms of the type and amount of input data needed to train the network. The quality characteristic to be observed is 'estimating accuracy' and maximising accuracy is the objective. The objective function to be minimised is the '% average absolute error'. Also of importance within the cost estimating area is the range of error, i.e. this is measured, during the current research, using the 'standard deviation of the % average absolute error values'.

The controllable design factors (i.e. parameters) to be considered along with their alternative levels are listed in Table 4.6. In the case of designing ANN structures the alternative 'levels' of the design factors will be represented by alternative types of mathematical functions used within processing elements. These factor levels define the experimental region to be studied.

Processing Element Function	Level 1	Level 2	Level 3
Summation Function	Sum	Majority	
Noise Function	Uniform noise	Gaussian noise	None
Transfer Function	Linear	TanH	Sine
Output Function	Direct	Select	One Highest
Error Function	Standard	Quadratic	Cubic
Learning Rules	Ext DBD	Perceptron	Delta Rule

Table 4.6 ANN Design Factors and Factor Levels

To select the appropriate orthogonal array to fit a specific case study, it is necessary to count the total degrees of freedom to find the minimum number of experiments that must be performed to reach a near optimum parameter set (American Supplier Institute Inc, 1989; Phadke, 1989; Wile, 1990). One degree of freedom is associated with the overall mean regardless of the number of control factors. To this is added the degrees of freedom associated with each control factor, which is equal to one less than the number of levels. For the drilling experimentation the number of degrees of freedom has been calculated in Table 4.7.

Processing Element Function	Number of Levels	Degrees of Freedom
Mean		1
Summation Function	2	1
Noise Function	3	2
Transfer Function	3	2
Output Function	3	2
Error Function	3	2
Learning Rules	3	2
	Total No. of Degrees of Freedom =	12

Table 4.7 Total Number of Degrees of Freedom

Experiment Numbers	Summation Functions	Noise Function	Transfer Function	Output Functions	Error Function	Learning Rules
1	Sum	Uniform noise	Linear	Direct	Standard	Ext DBD
2	Sum	Uniform noise	TanH	Select	Quadratic	Perceptron
3	Sum	Uniform noise	Sine	One highest	Cubic	Delta rule
4	Sum	Gaussian noise	Linear	Direct	Quadratic	Delta rule
5	Sum	Gaussian noise	TanH	Select	Cubic	Ext DBD
6	Sum	Gaussian noise	Sine	One highest	Standard	Perceptron
7	Sum	None	Linear	Select	Standard	Delta rule
8	Sum	None	TanH	One highest	Quadratic	Ext DBD
9	Sum	None	Sine	Direct	Cubic	Perceptron
10	Majority	Uniform noise	Linear	One highest	Cubic	Ext DBD
11	Majority	Uniform noise	TanH	Direct	Standard	Perceptron
12	Majority	Uniform noise	Sine	Select	Quadratic	Delta rule
13	Majority	Gaussian noise	Linear	Select	Cubic	Perceptron
14	Majority	Gaussian noise	TanH	One highest	Standard	Delta rule
15	Majority	Gaussian noise	Sine	Direct	Quadratic	Ext DBD
16	Majority	None	Linear	One highest	Quadratic	Perceptron
17	Majority	None	TanH	Direct	Cubic	Delta rule
18	Majority	None	Sine	Select	Standard	Ext DBD

Table 4.8 L18 Orthogonal Array Turning Cost Models

Therefore, it is necessary to conduct at least 12 experiments to reach a near optimum case. This fits into Taguchi's standard L18 array, shown in Table 4.8. In order for an array to be a viable choice, the number of rows must at least be equal to the degrees of freedom required (Phadke, 1989). The L18 array has 17 degrees of freedom and, hence, it can manage eight factors at 3 levels. Since we have only six control factors, two of the columns of the array will remain empty. Orthogonality is not lost by keeping one or more columns of an array empty (American Supplier Institute Inc, 1989; Phadke, 1989).

Using the same procedure for calculating the degrees of freedom the orthogonal array shown in Table 4.9 was generated for the *drilling* cost modelling experiments.

Experiment Numbers	Summation Functions	Noise Function	Transfer Function	Output Functions	Error Function	Learning Rules
1	Sum	Uniform noise	Linear	Direct	Standard	Hebb
2	Sum	Uniform noise	Sigmoid	Select	Quadratic	Perceptron
3	Sum	Uniform noise	Sine	One highest	Cubic	Delta rule
4	Sum	Gaussian noise	Linear	Direct	Quadratic	Delta rule
5	Sum	Gaussian noise	Sigmoid	Select	Cubic	Hebb
6	Sum	Gaussian noise	Sine	One highest	Standard	Perceptron
7	Sum	None	Linear	Select	Standard	Delta rule
8	Sum	None	Sigmoid	One highest	Quadratic	Hebb
9	Sum	None	Sine	Direct	Cubic	Perceptron
10	Majority	Uniform noise	Linear	One highest	Cubic	Hebb
11	Majority	Uniform noise	Sigmoid	Direct	Standard	Perceptron
12	Majority	Uniform noise	Sine	Select	Quadratic	Delta rule
13	Majority	Gaussian noise	Linear	Select	Cubic	Perceptron
14	Majority	Gaussian noise	Sigmoid	One highest	Standard	Delta rule
15	Majority	Gaussian noise	Sine	Direct	Quadratic	Hebb
16	Majority	None	Linear	One highest	Quadratic	Perceptron
17	Majority	None	Sigmoid	Direct	Cubic	Delta rule
18	Majority	None	Sine	Select	Standard	Hebb

Table 4.9 Orthogonal Array Drilling Cost Models

4.5 Effects of Number of Hidden Layers and Number of Processing Elements per Layer

The experiments listed in Tables 4.10 and 4.11 were carried out to determine the effects, on the accuracy of ANN based cost estimating models, of both:

i) the number of hidden layers within ANN structures, and

ii) the number of processing elements per layer.

Experiment Numbers	Number of Layers	Number of PEs per layer	Model Types Tested
1 to 20	1	1 to 10	Best ANN, Worst ANN
21 to 40	2	1 to 10	Best ANN, Worst ANN
41 to 60	3	1 to 10	Best ANN, Worst ANN

Table 4.10 Number of Hidden Layers Experimentation

Experiments Numbers	Number of PEs per Layer	Number of Layers	Model Types Tested
1 to 6	1	1, 2, 3	Best ANN, Worst ANN
7 to 12	2	1, 2, 3	Best ANN, Worst ANN
13 to 18	10	1, 2, 3	Best ANN, Worst ANN

Table 4.11 Number of PEs per Layer Experimentation

4.6 Effects of Number of Variables and Size of Data Sample

The experiments listed in Table 4.12 and 4.13 were carried out to determine the effects, on the accuracy of ANN based cost estimating models, of both:

i) of the number of variables used to construct models, and

ii) of the number of data samples used to develop the cost models.

As a comparison models were also developed using the LINEST Regression Analysis Function within Microsoft Excel Spreadsheet (Microsoft Excel 97 User Manual, 1997).

Experiment Numbers	Number of Variables	Number of Data Points	Model Types Tested
1 to 15	1	150, 300, 450, 600, 750	Best ANN, Worst ANN, Regression
16 to 30	2	150, 300, 450, 600, 750	Best ANN, Worst ANN, Regression
31 o 45	4	150, 300, 450, 600, 750	Best ANN, Worst ANN, Regression
46 to 60	6	150, 300, 450, 600, 750	Best ANN, Worst ANN, Regression
61 to 75	9	150, 300, 450, 600, 750	Best ANN, Worst ANN, Regression
76 to 90	16	150, 300, 450, 600, 750	Best ANN, Worst ANN, Regression

Table 4.12 Number of Variables Experimentation

Experiment Numbers	No. of Data Points	Number of Variables	Model Types Tested
1 to 18	150	1, 2, 4, 6, 9, 16	Best ANN, Worst ANN, Regression
19 to 36	300	1,2 , 4, 6, 9, 16	Best ANN, Worst ANN, Regression
37 to 54	450	1, 2, 4, 6, 9, 16	Best ANN, Worst ANN, Regression
55 to 72	600	1, 2, 4, 6, 9, 16	Best ANN, Worst ANN, Regression
73 to 90	750	1, 2, 4, 6, 9, 16	Best ANN, Worst ANN, Regression

Table 4.13 Number of Data Points Experimentation

4.7 Comparison of Best and Worst Turning and Drilling Models

In order to compare the performance of ANN models for costing other types of processes than they were originally developed for, the following additional comparisons were performed, i.e.:

i) drilling and turning regression models,

ii) best and worst turning models using turning test data,

iii) best and worst turning models using the drilling test data,

iv) best and worst drilling models using the drilling test data, and

v) best and worst drilling models using the turning test data.

Chapter 5 Experimental Results

5.1 Results of Taguchi Analysis

In order to identify the relative effect on estimating accuracy of individual PE types, and hence determine the best and worst ANN structures, the experiments listed in Tables 4.8 and 4.9 were carried out. For all experiments the maximum training, (i.e. 750 data points) and maximum testing (i.e. 350 data points) sets were used. Table 5.1 lists the results, in terms of % Average Absolute Error, which returns the average of a set of errors, of the ANN costing models developed for both the turning and drilling applications.

Turning			**Drilling**		
PE Functions		**Effect of PE Function on % Ave Abs Error**	**PE Functions**		**Effect of PE Function on % Ave Abs Error**
Summation Function	**Sum**	29.50	**Summation Function**	**Sum**	12.43
	Majority	32.70		**Majority**	12.48
Noise Function	**Uniform**	29.31	**Noise Function**	**Uniform**	12.41
	Gaussian	29.31		**Gaussian**	12.38
	None	34.70		**None**	12.58
Transfer Function	**Linear**	30.30	**Transfer Function**	**Linear**	12.73
	Sine	33.97		**Sine**	12.14
	TanH	29.05		**Sigmoid**	12.50
Output Function	**Direct**	29.05	**Output Function**	**Direct**	13.09
	Select	30.30		**Select**	12.67
	One Highest	33.97		**One highest**	11.61
Error Function	**Standard**	29.05	**Error Function**	**Standard**	12.68
	Quadratic	33.97		**Quadratic**	12.12
	Cubic	30.30		**Cubic**	12.58
Learning Rule	**Delta rule**	32.75	**Learning Rule**	**Delta rule**	11.93
	Perceptron	33.23		**Perceptron**	13.47
	Ext DBD	27.34		**Hebb**	11.97

Table 5.1 Effect of PE Functions on % Average Absolute Error

5.1.1 Turning Application

After selecting an appropriate orthogonal array, Table 4.8, eighteen experiments have been carried out in order to find the best and worst ANN structures for the turning model. Figures 5.1 to 5.6 compares, for each type of PE function, the relative effects of the alternative types of each function examined, and clearly differentiates between the best and worst NN structures listed in Table 5.2.

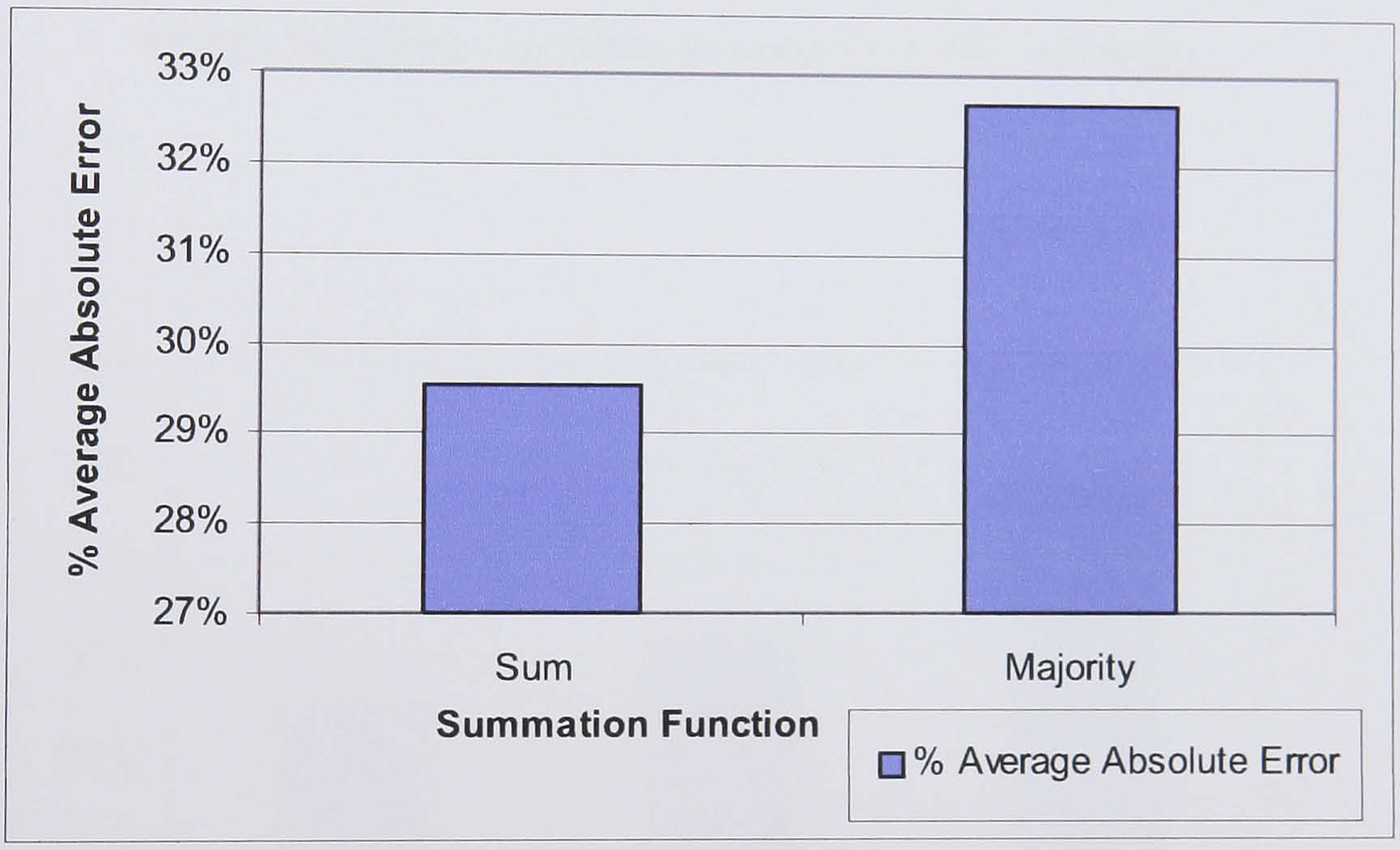

Figure 5.1 Turning - Comparison of Summation Functions

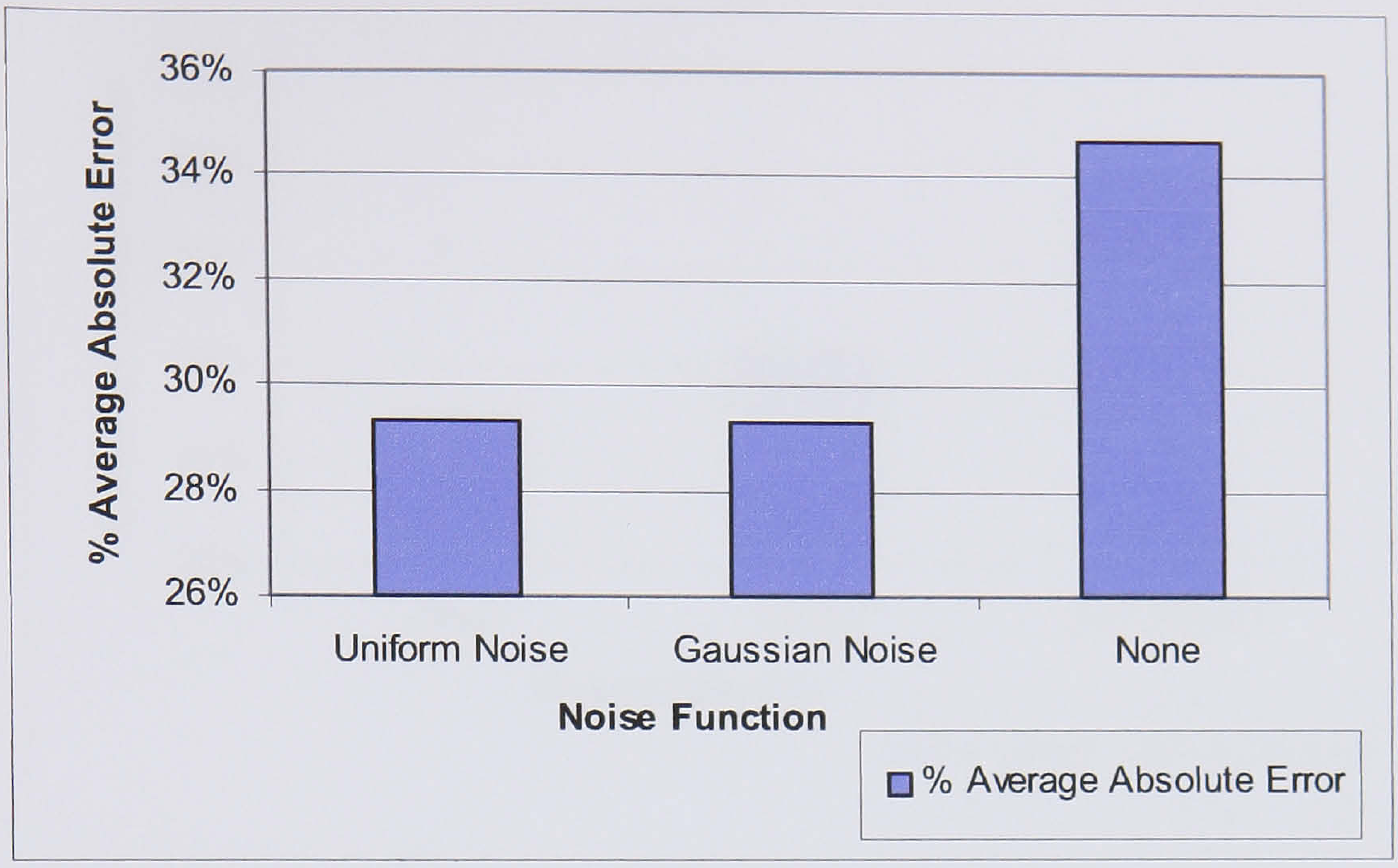

Figure 5.2 Turning - Comparison of Noise Functions

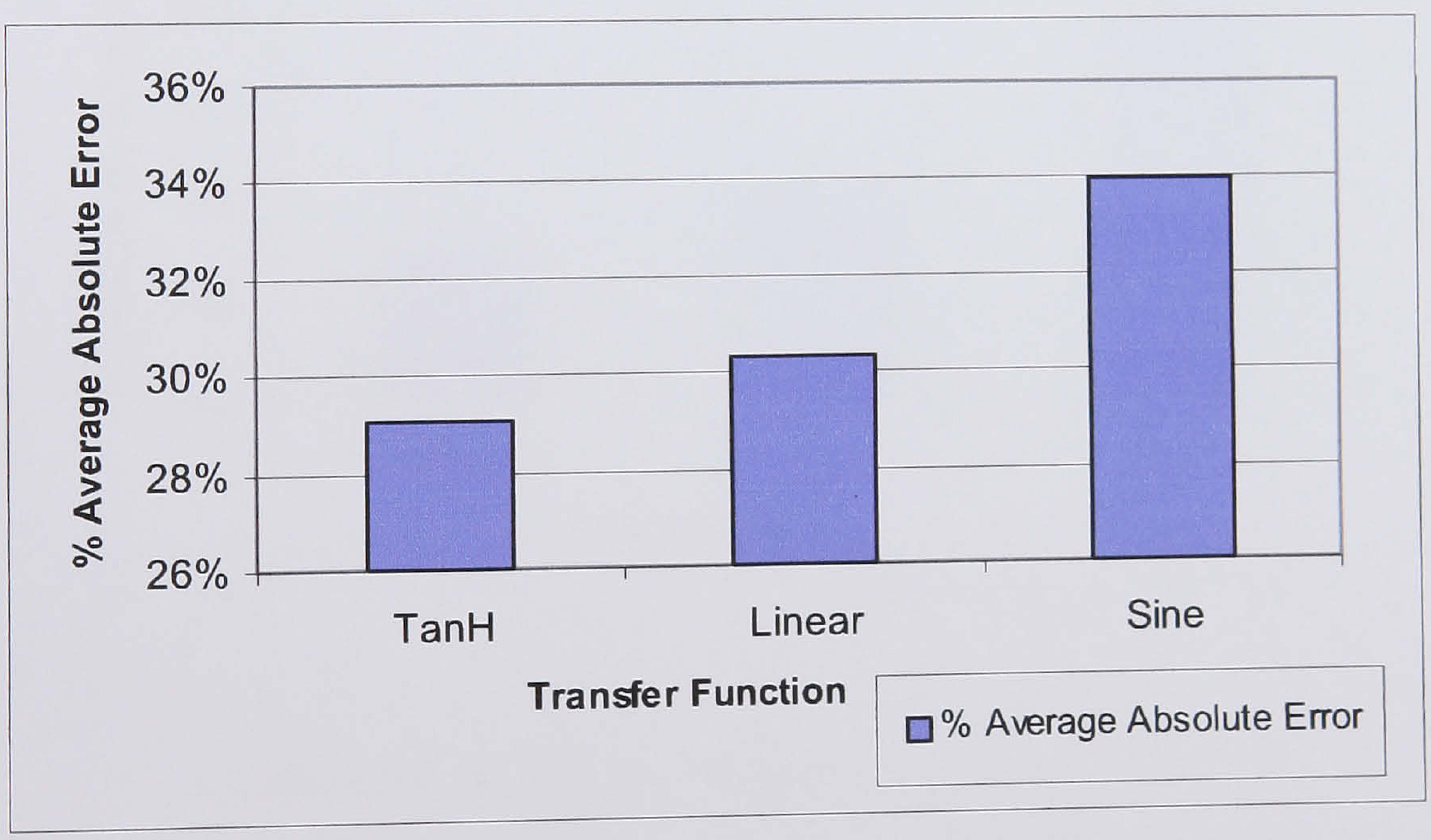

Figure 5.3 Turning - Comparison of Transfer Functions

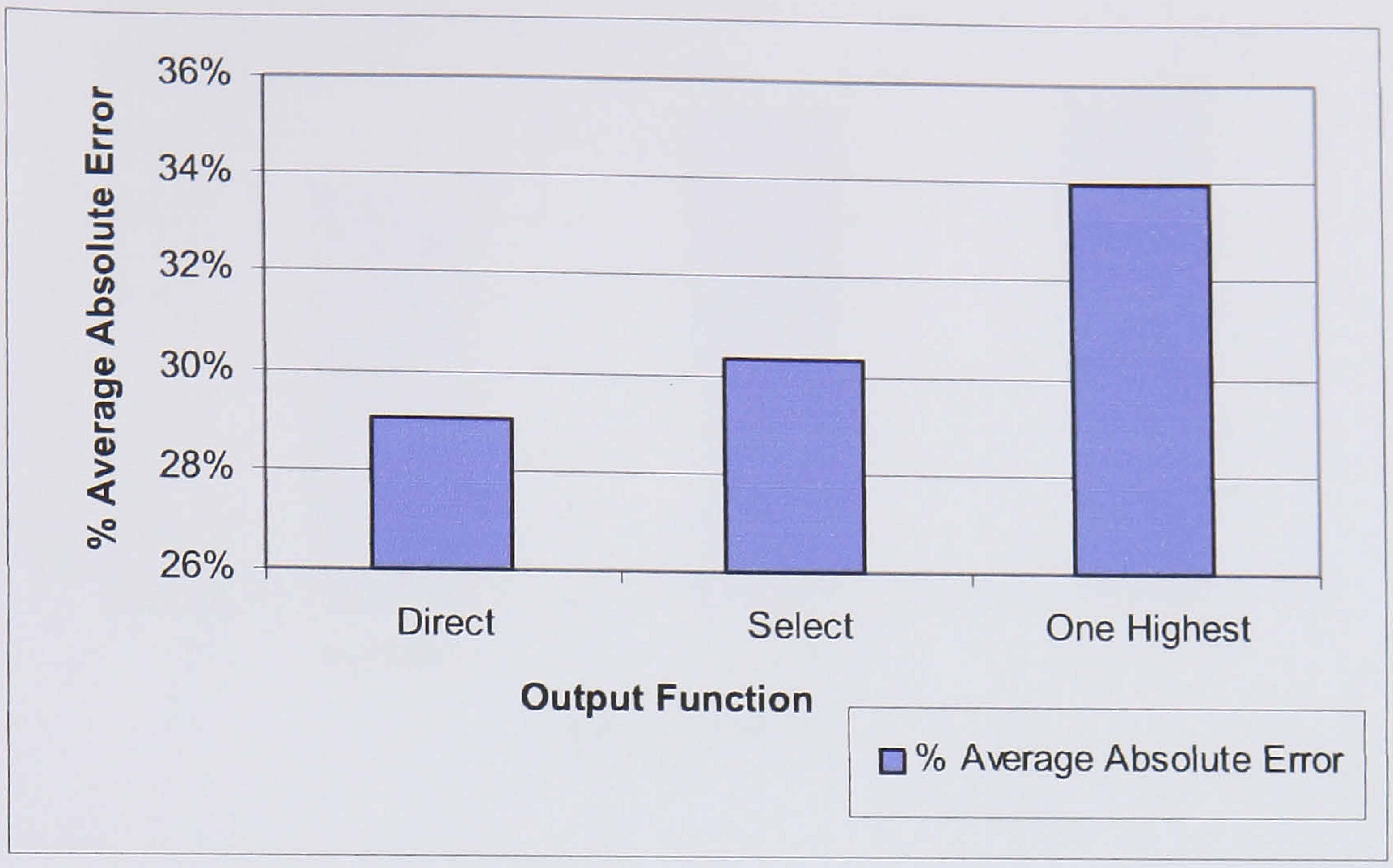

Figure 5.4 Turning - Comparison of Output Functions

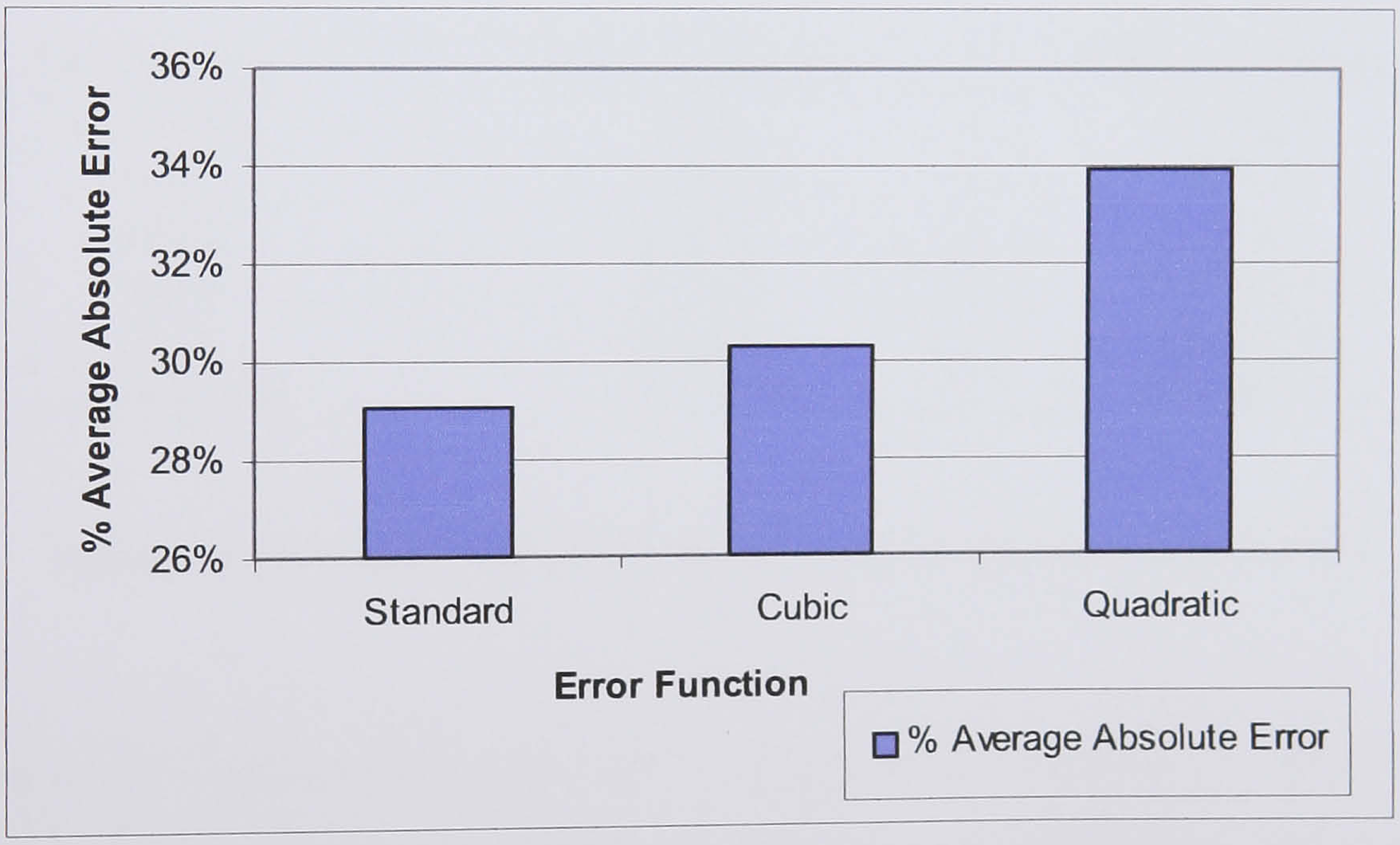

Figure 5.5 Turning - Comparison of Error Functions

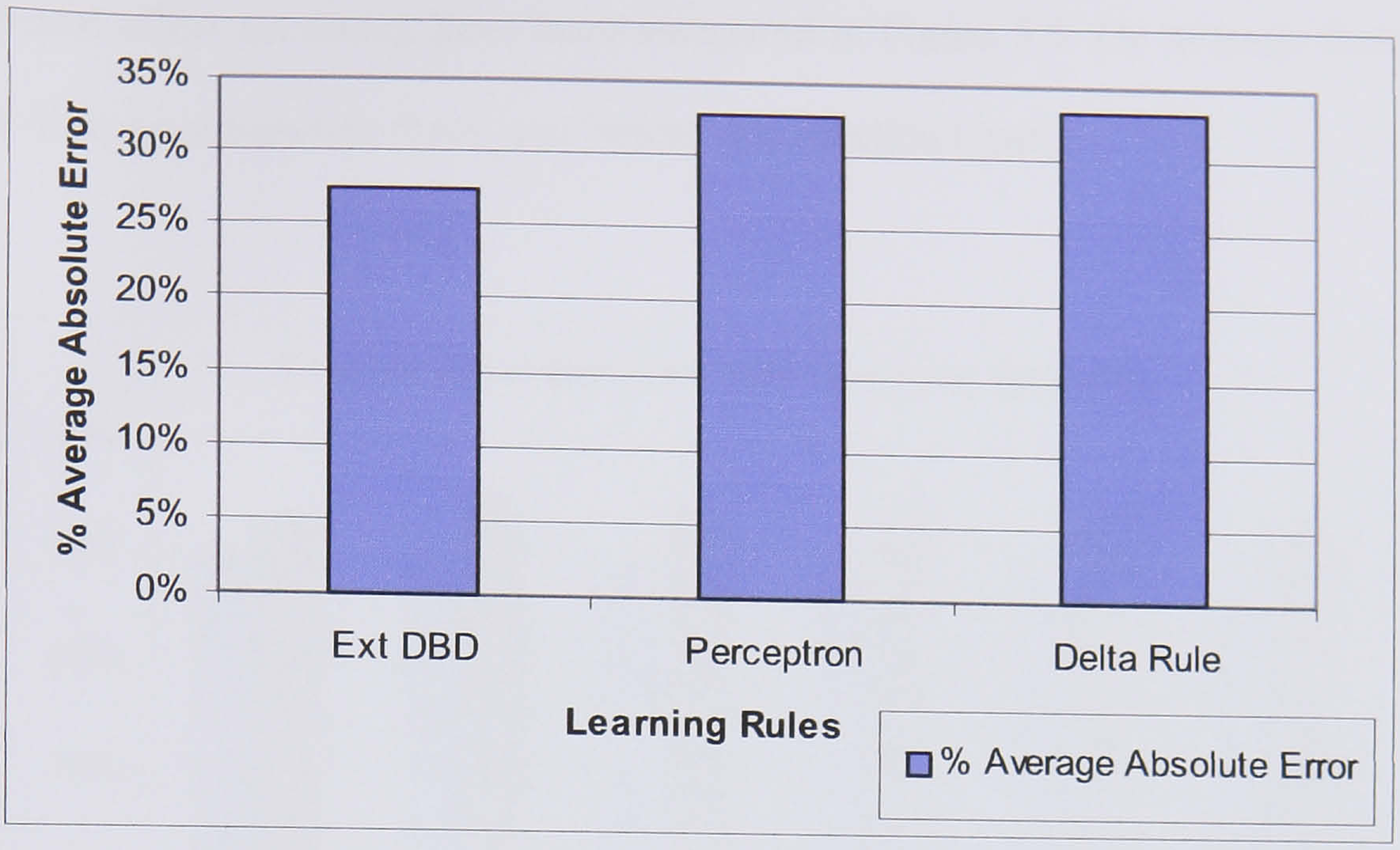

Figure 5.6 Turning - Comparison of Learning Rules

PE Function	Best Conditions	Worst Conditions
Summation	Sum	Majority
Noise	Uniform	None
Transfer	TanH	Sine
Output	Direct	One-Highest
Error	Standard	Quadratic
Learning Rule	Ext DBD	Perceptron

Table 5.2 Best and Worst ANN Structures for Turning Application

By use of the Taguchi method the number of experiments required to establish these structures has been greatly decreased, i.e. a full factorial analysis would have required 729 (3^6) experiments compared with the 18 experiments actually undertaken. Hence, it has been demonstrated that the Taguchi method is an effective methodology for reducing the amount of time and effort required in designing ANN structures. From Table 5.1 the 'best' function types, (i.e. the function types causing the least amount of error), and the 'worst' function types, (i.e. the function types having the most detrimental effect on error), have been compared in Figure 5.7. On average there is a 4.87% difference between 'best' and 'worst' PE function types.

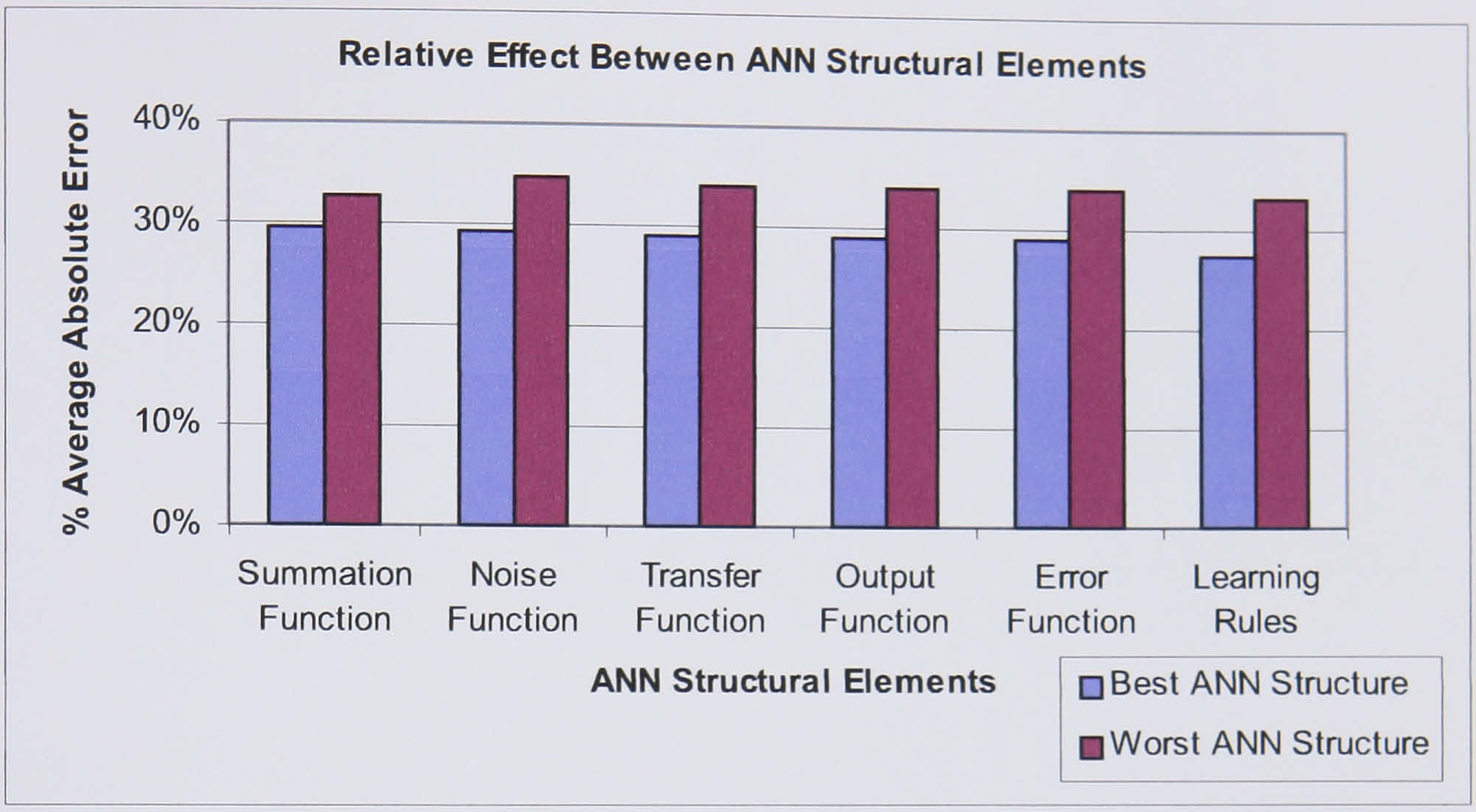

Figure 5.7 Comparison of Best and Worst PE Function Types

5.1.2 Drilling Application

Using the orthogonal array as show in Table 4.9, eighteen experiments have been carried out in order to find the best and worst ANN structures for the drilling model. Figures 5.8 to 5.13 compares, for each type of PE function, the relative effect of the alternative types of each function examined, and again clearly differentiates between the best and worst ANN structures have been compared in Figure5.14.

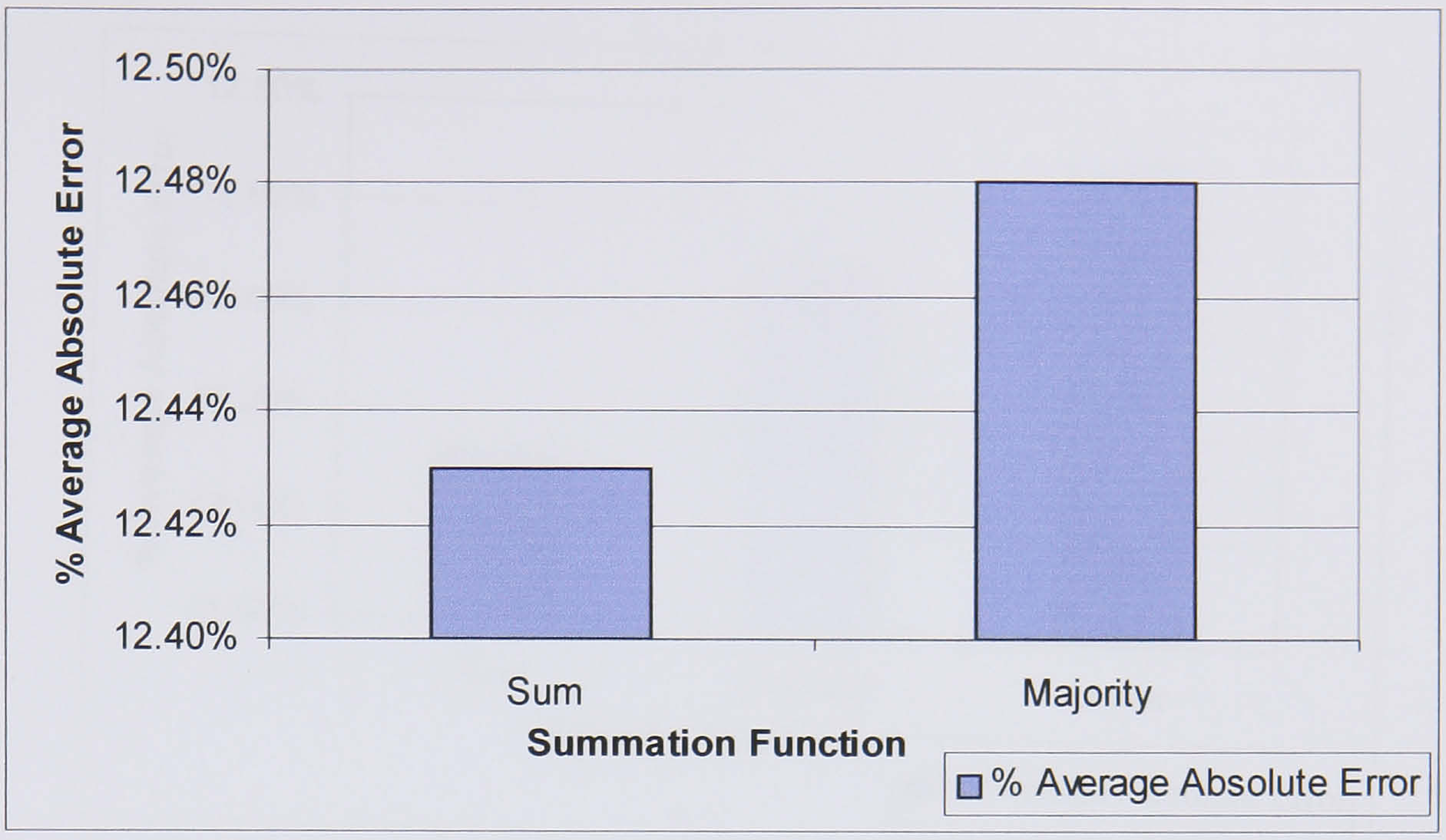

Figure 5.8 Drilling - Comparison of Summation Functions

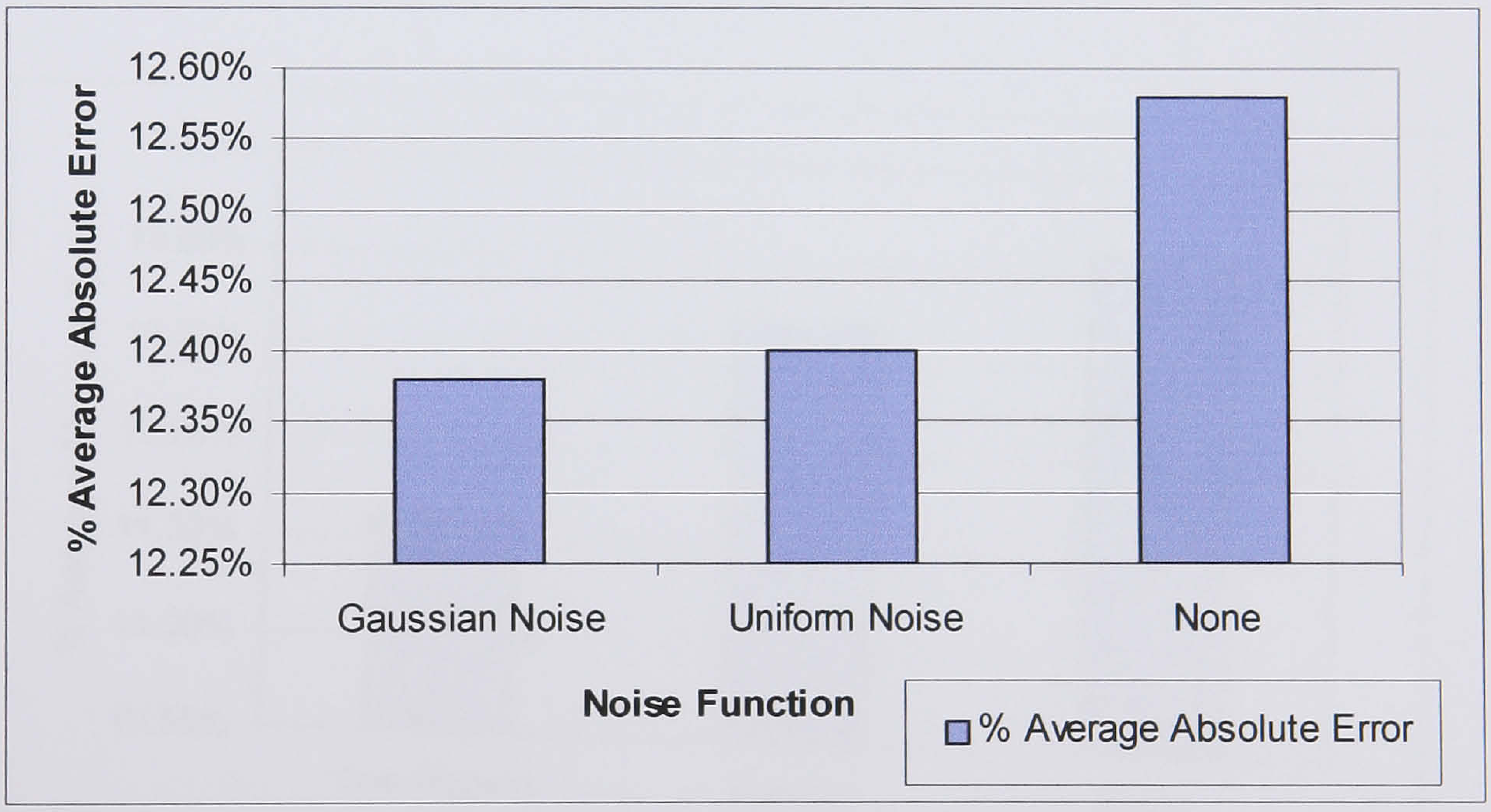

Figure 5.9 Drilling - Comparison of Noise Functions

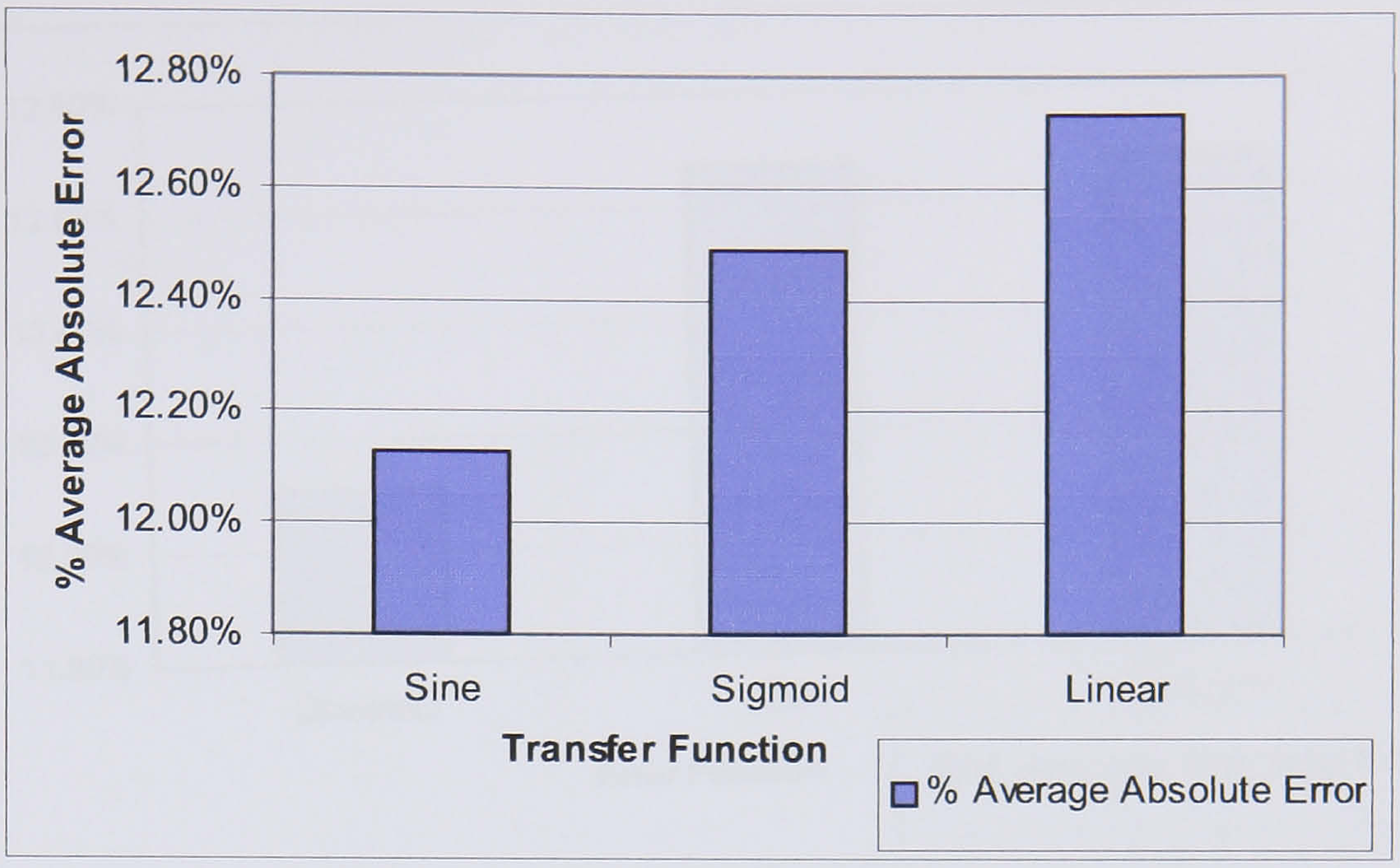

Figure 5.10 Drilling - Comparison of Transfer Functions

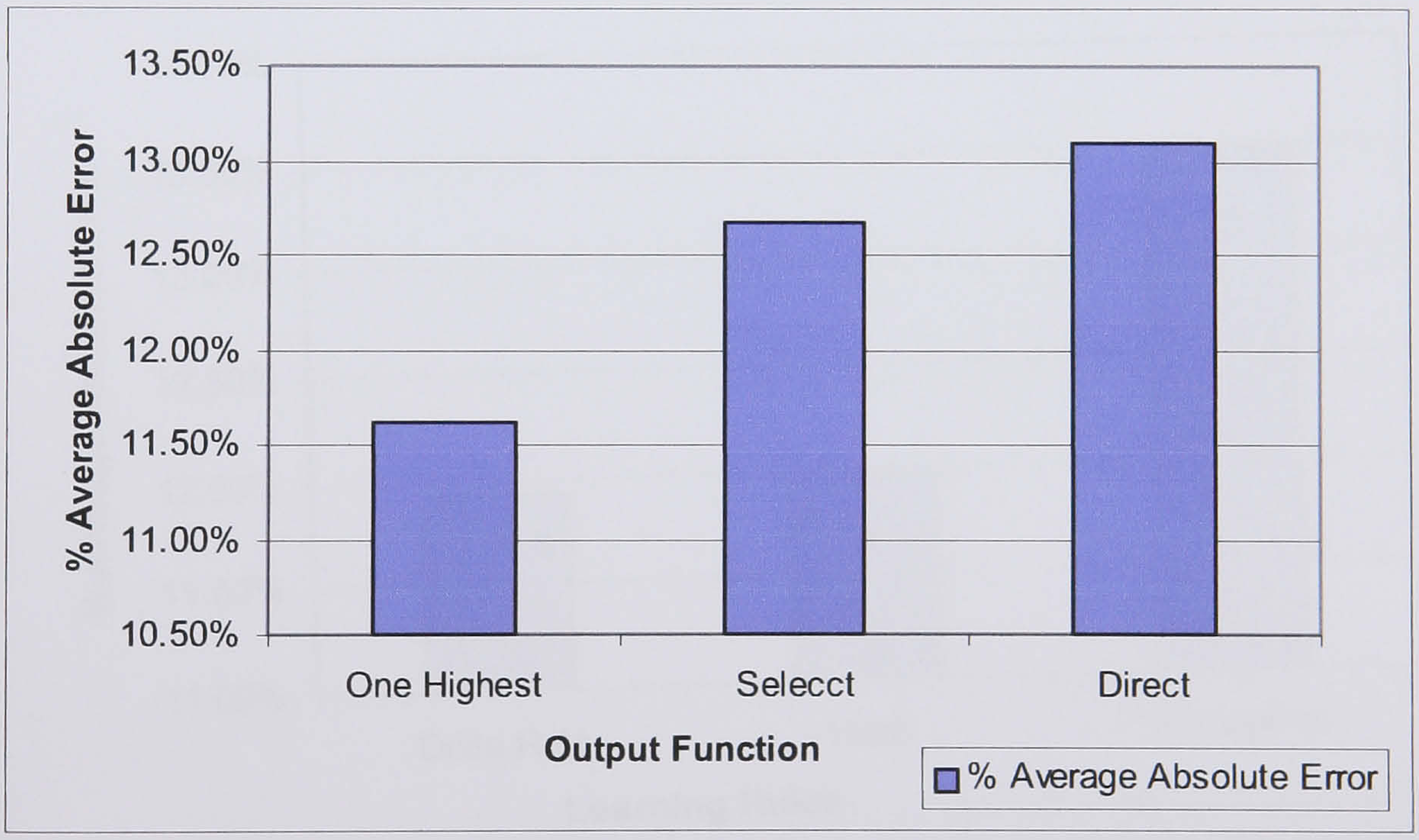

Figure 5.11 Drilling - Comparison of Output Functions

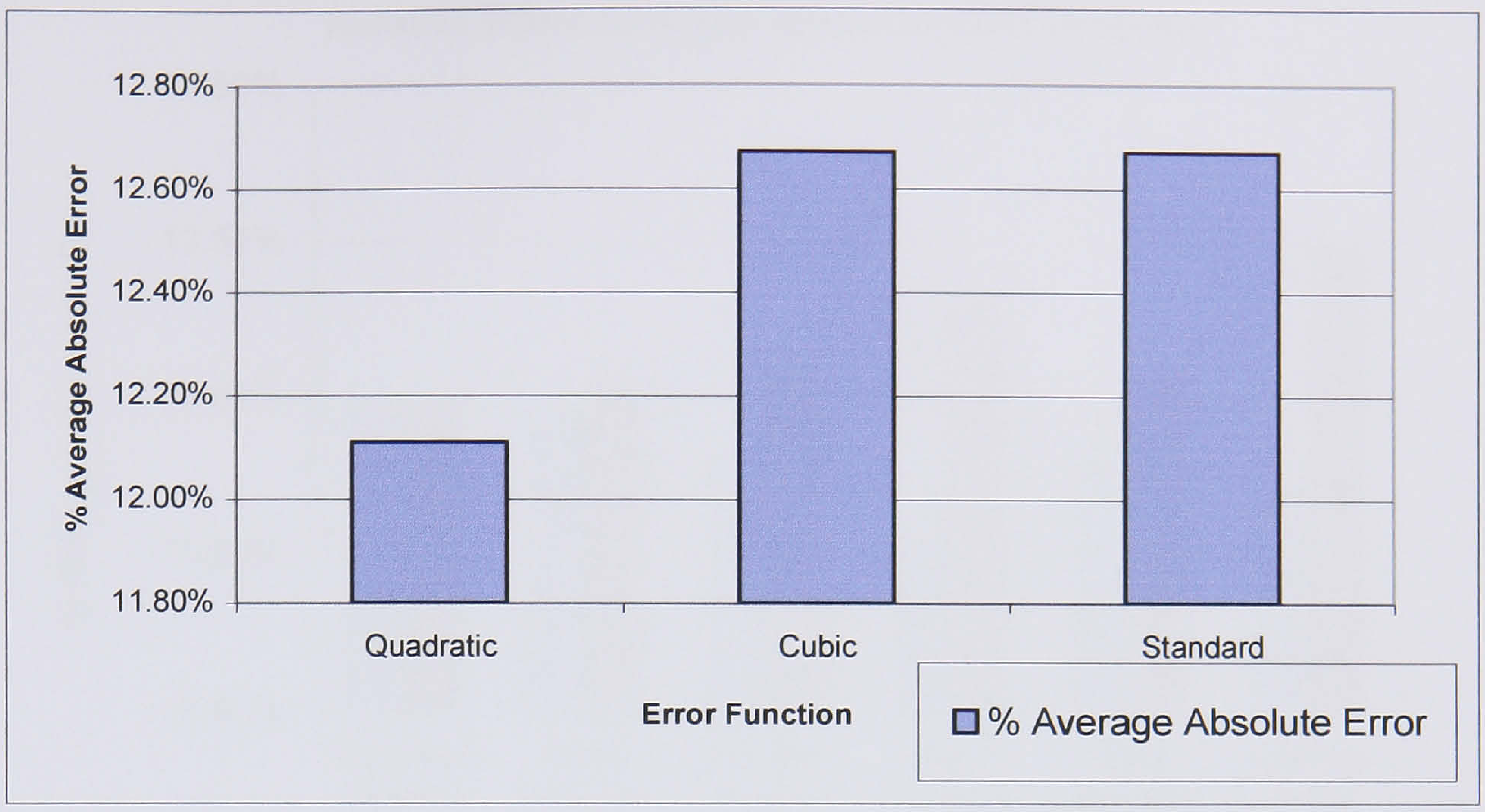

Figure 5.12 Drilling - Comparison of Error Functions

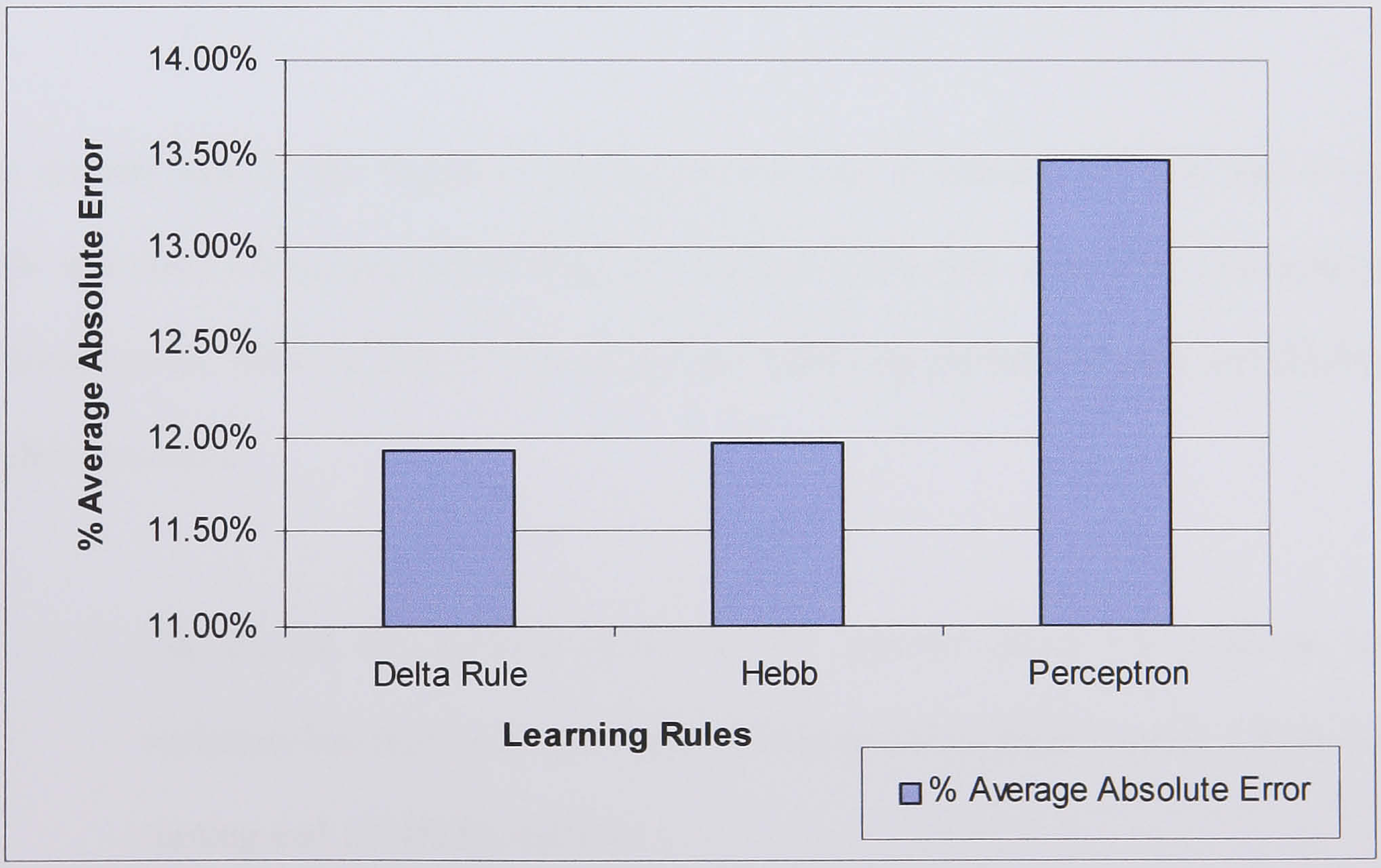

Figure 5.13 Drilling - Comparison of Learning Rules

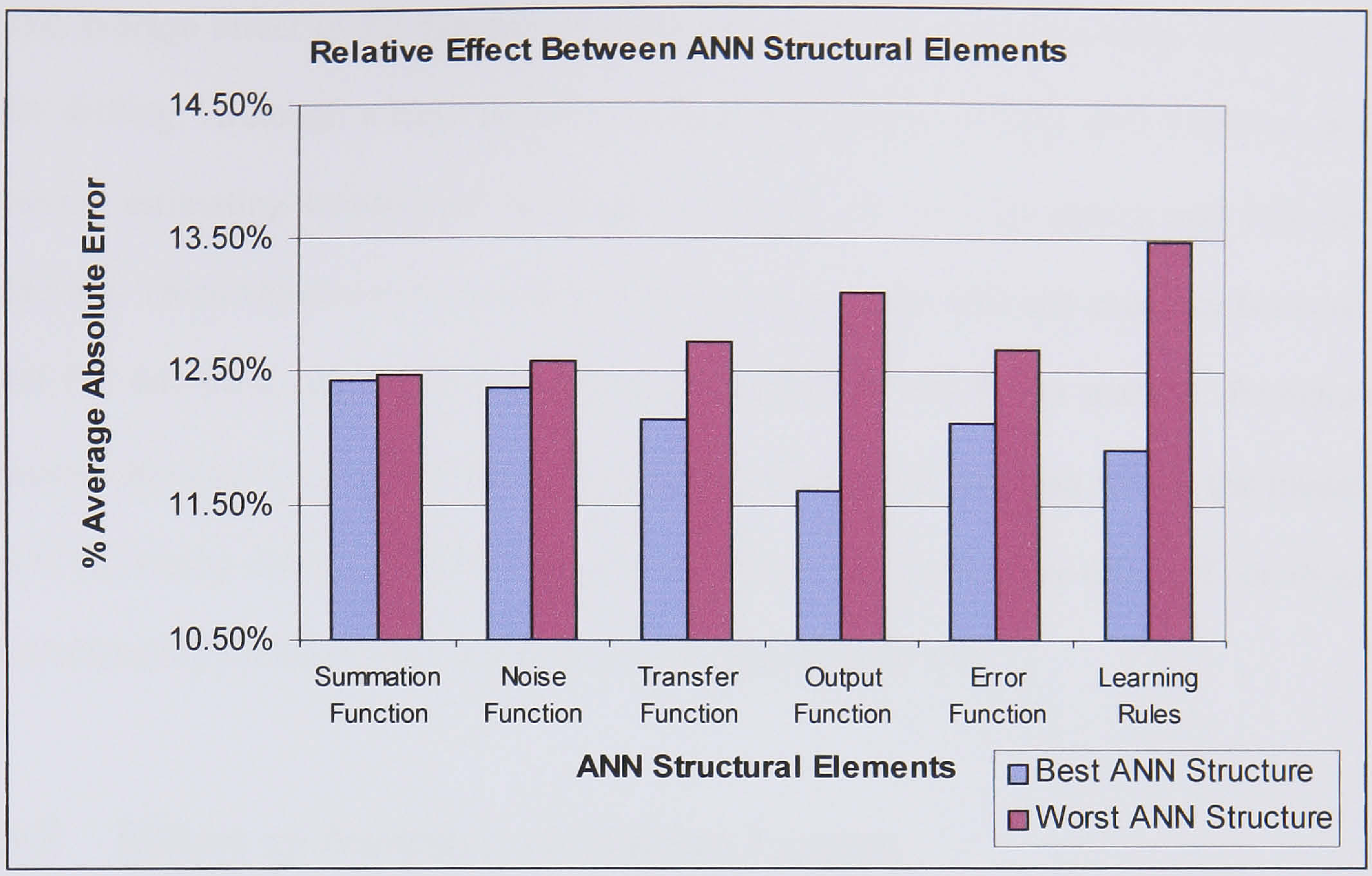

Figure 5.14 Comparison of Best and Worst PE Function Types

The primary aim of the Taguchi experimentation was to identify the best and worst ANN structures for turning and drilling applications. However, a detailed examination of these results, listed in Table 5.1 provides the following for both turning and drilling application areas:

1. The choice of Learning Rules has the greatest effect on accuracy, i.e. variation between best and worst Learning Rules types equals 5.89% for turning and 1.54% for drilling.
2. The choice of Summation Function has the least effect on accuracy, i.e. variation between best and worst Summation Function types equals 3.2% for turning and 0.05% for drilling.

The average effect of PE function types on accuracy is 31.1% for turning and 12.5% for drilling. Although a large difference exists this appears to have little effect on the overall estimating accuracy of the resulting models, i.e. 18% for turning and 16% for drilling. There appears to be no discernible reason why the different accuracy between the PE functions types and overall costing models should be so marked. Potential factors that may account for this effect are the number of variables within the model (i.e. 16 turning variables and 4 drilling variables), and/or the relative effect of variables on estimating accuracy, (i.e. as shown in Figures 5.44 and 5.45).

5.2 Effect of Number of Hidden Layers

In order to identify the relative effect on cost modelling estimating accuracy of the *number of hidden layers* the experiments listed in Table 4.10 were carried out. The results obtained are shown in Figures 5.15 to 5.16. For all experiments the maximum training, (i.e. 750 data points) and maximum testing (i.e. 350 data points) sets were used.

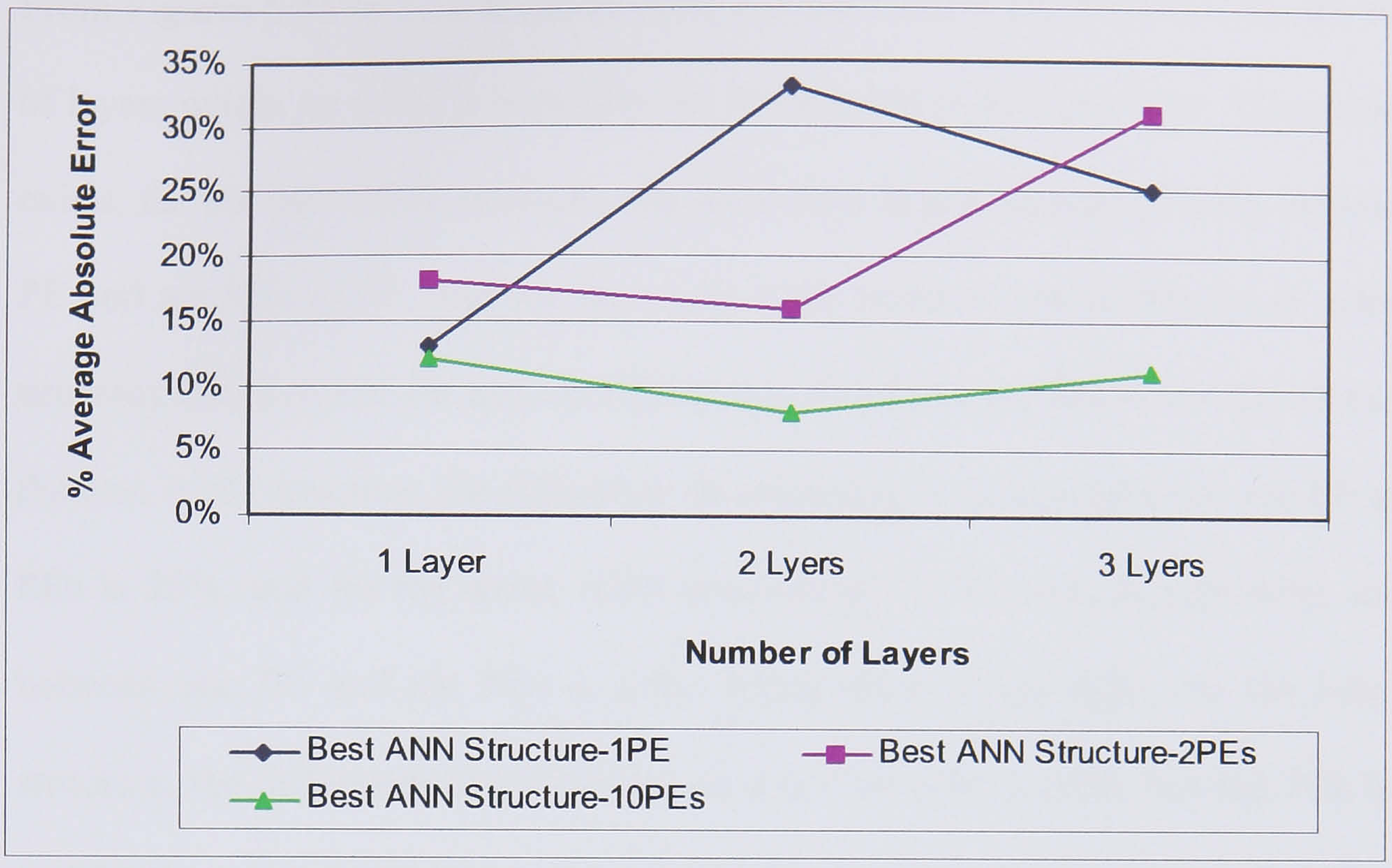

Figure 5.15 Effect of Increasing Number of Layers

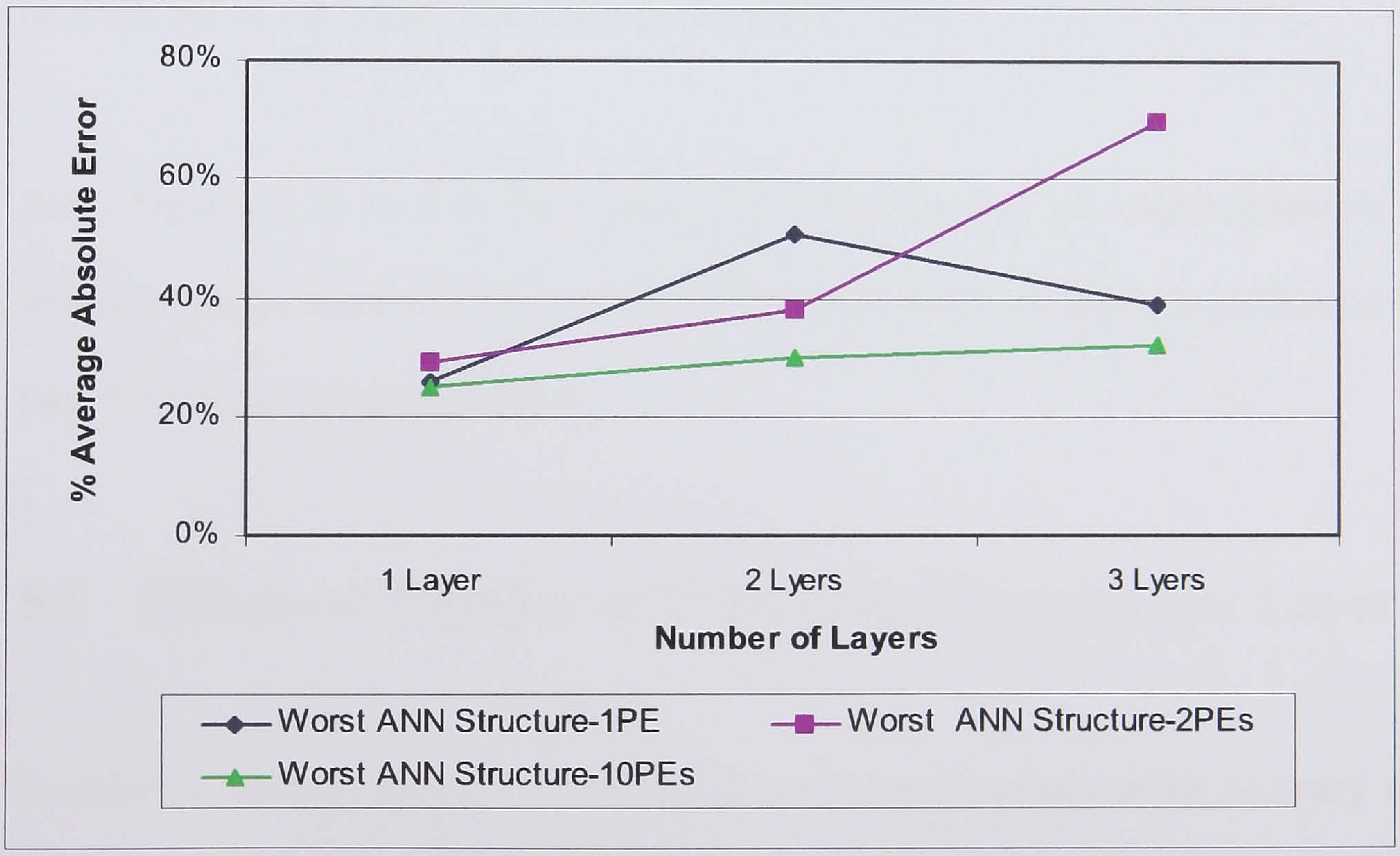

Figure 5.16 Effect of Increasing Number of Layers

From Figures 5.15 to 5.16 it can be seen that the relative effect of varying the number of layers within an ANN is dependent on the number of PEs per layer. When one layer exists, for the best ANN structure, the difference in estimating accuracy between one PE and ten PEs is 6%, and for the worst ANN structure the difference in estimating accuracy between one PE and ten PEs is only 4% different. When two layers exist, for the best ANN structure, the difference in estimating accuracy between one PE and ten PEs is 25%, and for the worst ANN structure the difference in estimating accuracy between one PE and ten PEs is 21%. When three layers exist, for the best ANN structure, the difference in estimating accuracy between one PE and ten PEs is 20%, and for the worst ANN structure the difference in estimating accuracy between one PE and ten PEs is 38%. Overall increasing the number of layers within an artificial neural network led to a decrease in estimating accuracy.

From Figures 5.15 to 5.16 the consequences of choosing an inappropriate network structure can be observed, i.e. in all cases the 'best' network structure performed better then the 'worst' network structure.

5.3 Effects of Number of Processing Elements per Layer

In order to identify the relative effect on cost modelling estimating accuracy of the *number of processing elements per layer* the experiments listed in Table 4.11 were carried out. The results obtained are shown in Figures 5.17 to 5.19. For all experiments the maximum training, (i.e. 750 data points) and maximum testing (i.e. 350 data points) sets were used.

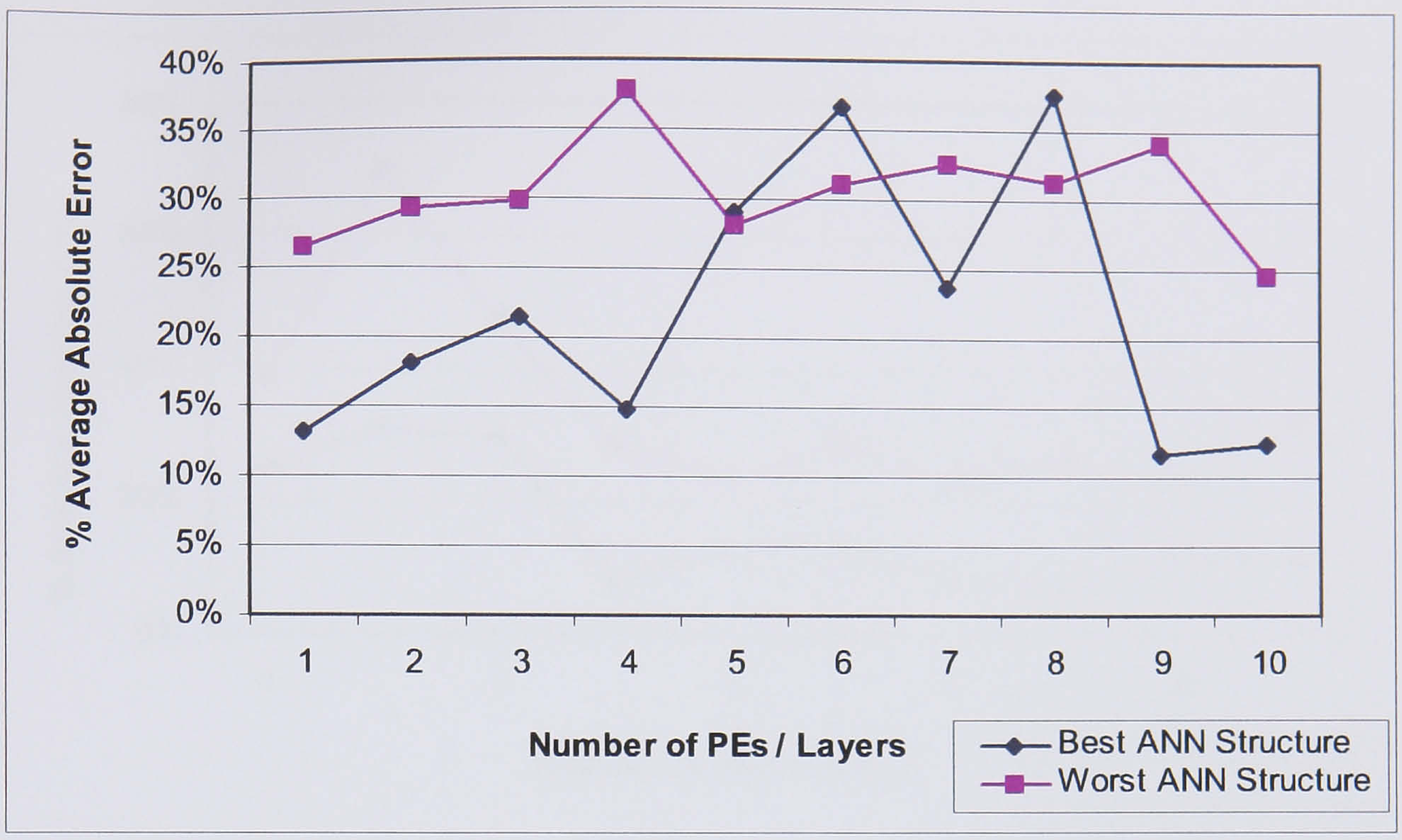

Figure 5.17 Effect of Number of PEs/Layer-1 Layer

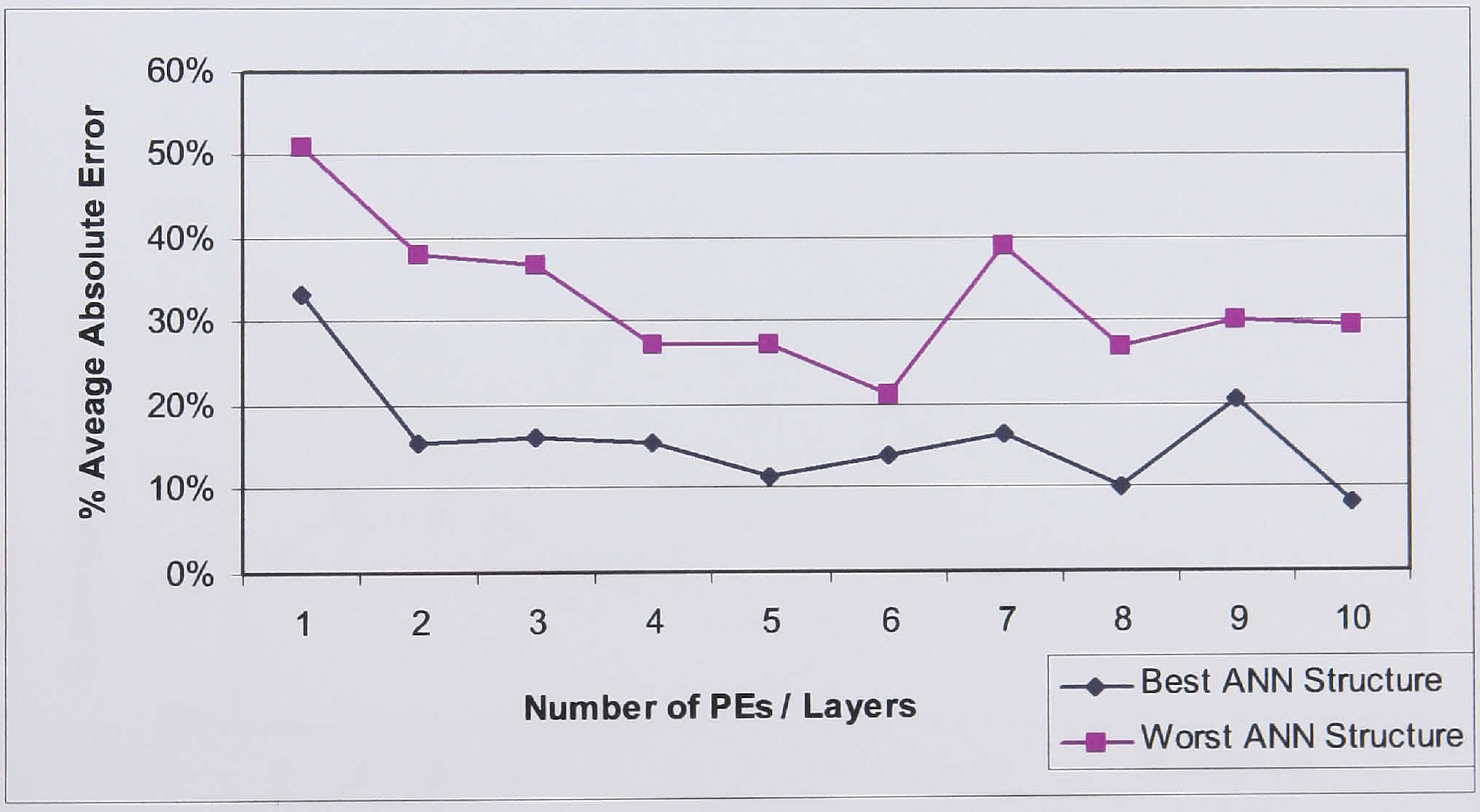

Figure 5.18 Effect on Number of PEs/ Layer -2 Layers

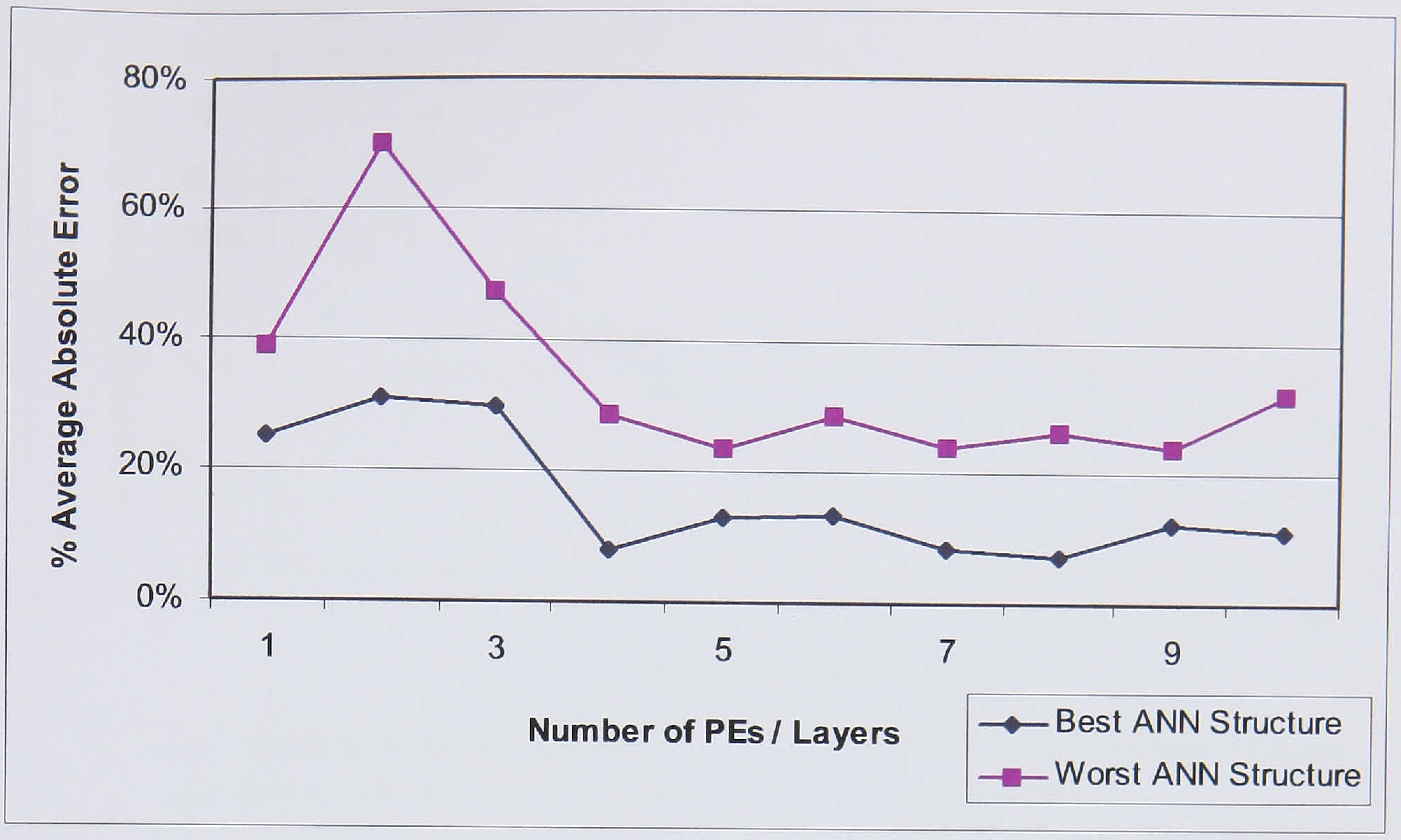

Figure 5.19 Effect on Number of PEs/ Layers - 3 Layers

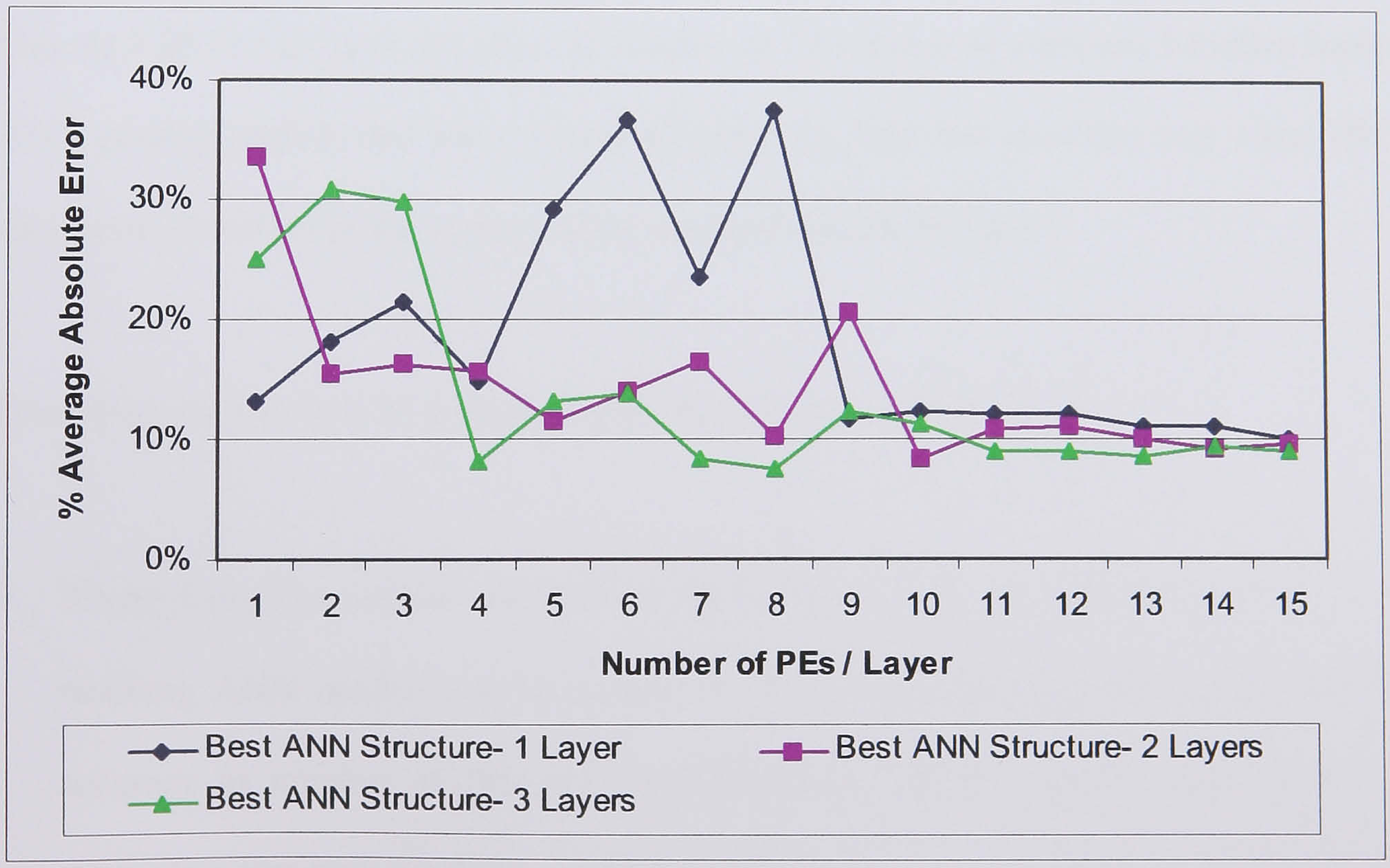

Figure 5.20 Effect of Number of PEs/ Layer with 3 Layers/Best ANN Structure

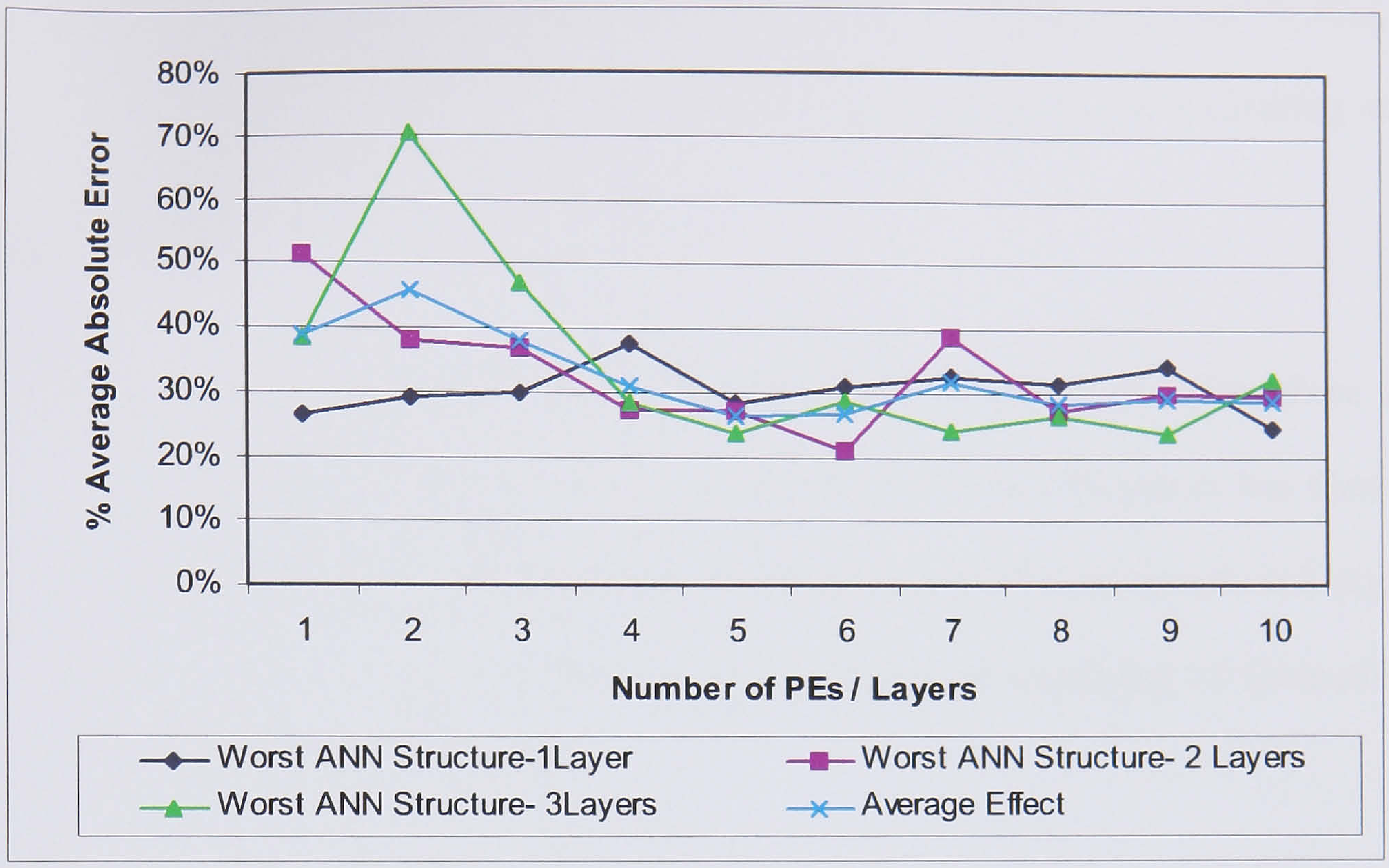

Figure 5.21 Effect of Number of PEs/ Layer with 3 Layers/Worst ANN Structure

Figures 5.20 to 5.21 uses *the effect of number of PEs/ Layer* to compare 3-hidden layer ANN costing models that are constructed using the best NN structure and worst NN structures identified in the experimental results shown in Table 5.1.

From Figures 5.17 to 5.21 the following effects can be observed, i.e.:

1. Where networks contain one hidden layer, Figure 5.17, the estimating ability of the resulting ANN models can be erratic, i.e. there is no discernible trend in estimating accuracy as number of PEs per layer increases. There is also a large variation in estimating accuracy, i.e. between 12% and 37%.

2. Where networks contain two hidden layers, Figure 5.18, there is an initial increase in estimating accuracy from 1 PE/layer to 2 PEs/layer but thereafter there is no

discernible difference when additional PEs are introduced. There is also, when 2 or more PEs/layer are used, a marked decrease in variability of estimating accuracy, i.e. between 9% and 20%.

3. Where networks contain three hidden layers, Figure 5.19, again there is an initial increase in estimating accuracy from 3 PEs/layer to 4 PEs/layer but there after again there is no discernible difference when additional PEs are introduced. Again there is, when 4 or more PEs/layer are used, a decrease in variability of estimating accuracy, i.e. between 7% and 17%.

4. In Figure 5.20 the relative effect of varying the number of PEs/layer is compared between 1-layer, 2-layer and 3-layer networks. Overall the 3-layer network provides the highest estimating accuracy.

These results reinforce the need to choose network structures with care, i.e. in all cases the 'best' network structure again performed better then the 'worst' network structure.

5.4 Effect of Number of Variables and Size of Data Sample

The best and worst NN structures were selected from Table 5.1 and experiments carried out to identify the effects on estimating accuracy of variations in the number of variables and number of data points used to construct ANN models. As a comparison, models were also developed using the LINEST regression analysis function within the Microsoft Excel Spreadsheet package (Microsoft Excel User Manual, 1997).

5.4.1 Estimating Accuracy Vs Number of Data Points

Figures 5.22 to 5.27 show the effect on the % average absolute error of varying the number of data points used to construct models whilst Figures 5.28 to 5.33 show the effect on the standard deviation in % average absolute errors. It is a measure of how widely values are dispersed from the average value.

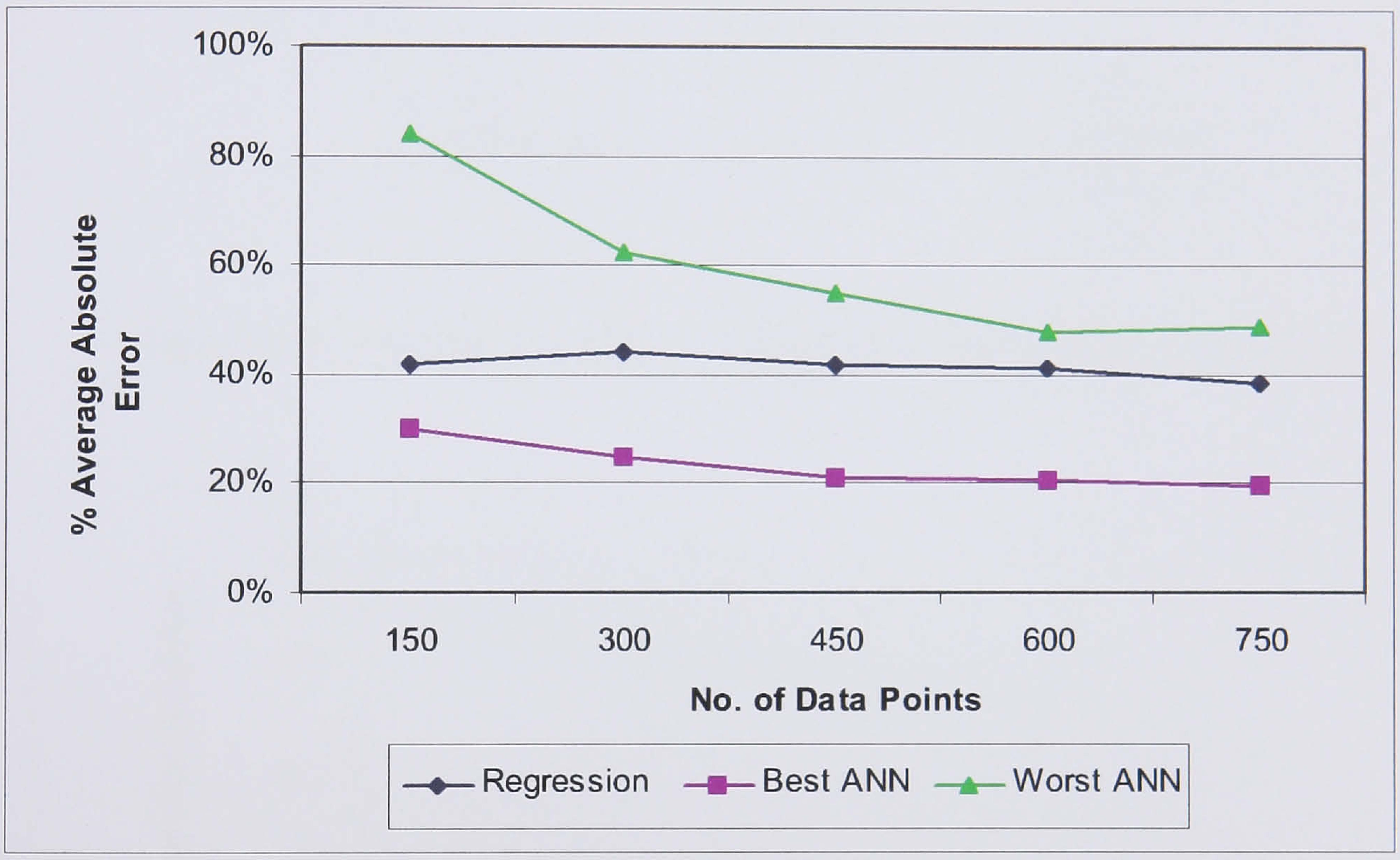

Figure 5.22 Average Accuracy Vs Number of Data Points – 1 Variable

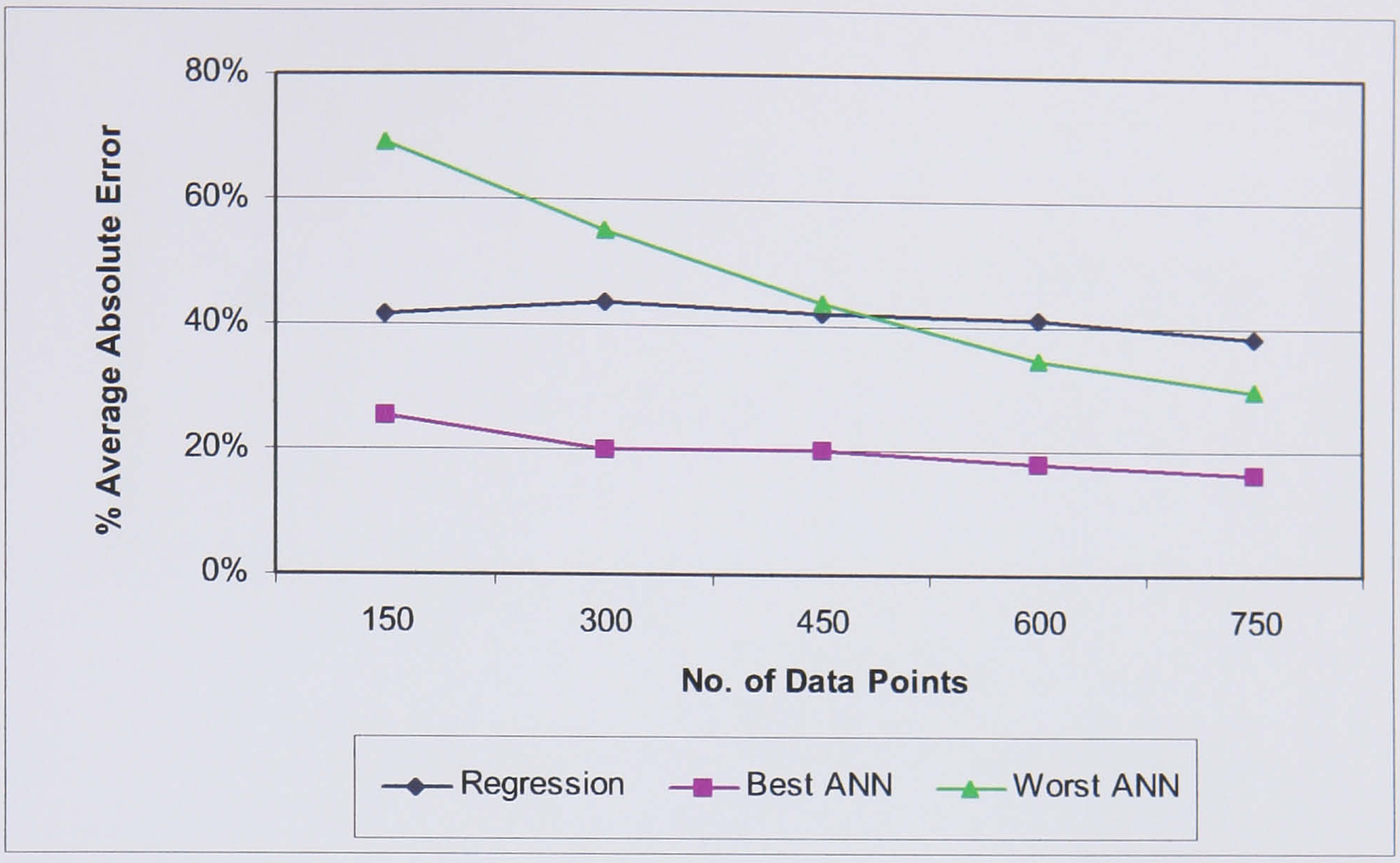

Figure 5.23 Average Accuracy Vs Number of Data Points – 2 Variables

Figure 5.24 Average Accuracy Vs Number of Data Points – 4 Variables

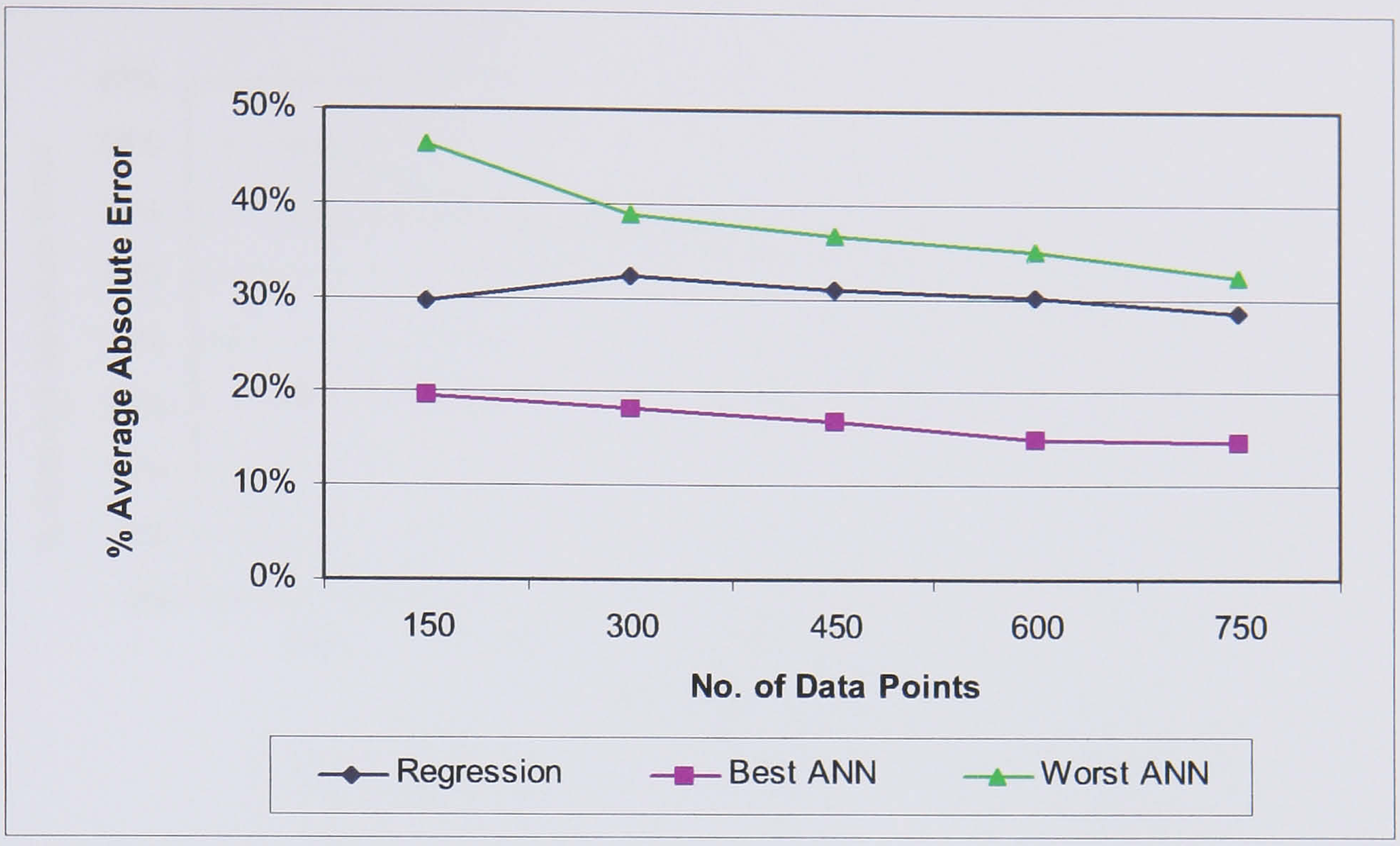

Figure 5.25 Average Accuracy Vs Number of Data Points – 6 Variables

Figure 5.26 Average Accuracy Vs Number of Data Points – 9 Variables

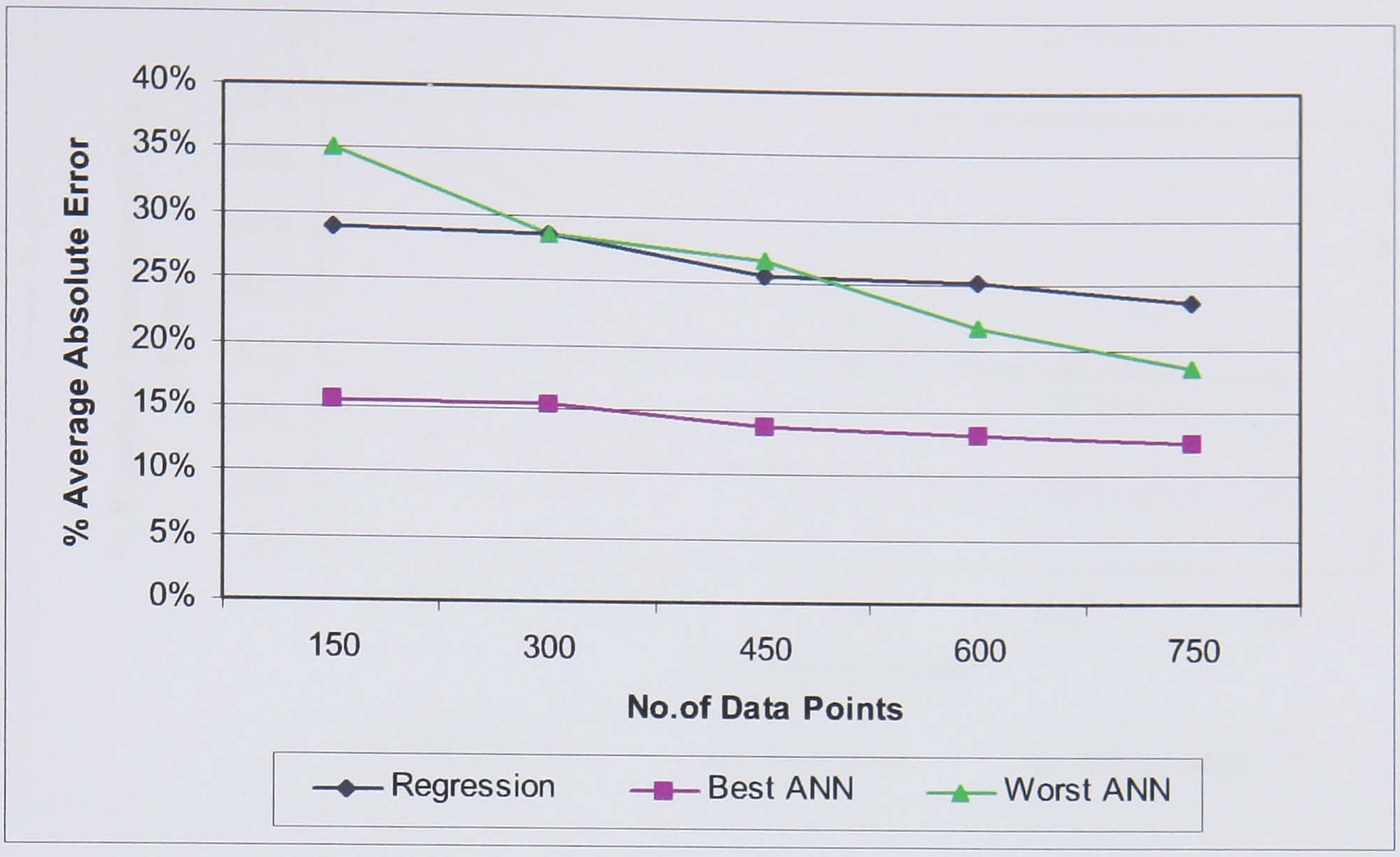

Figure 5.27 Average Accuracy Vs Number of Data Points – 16 Variables

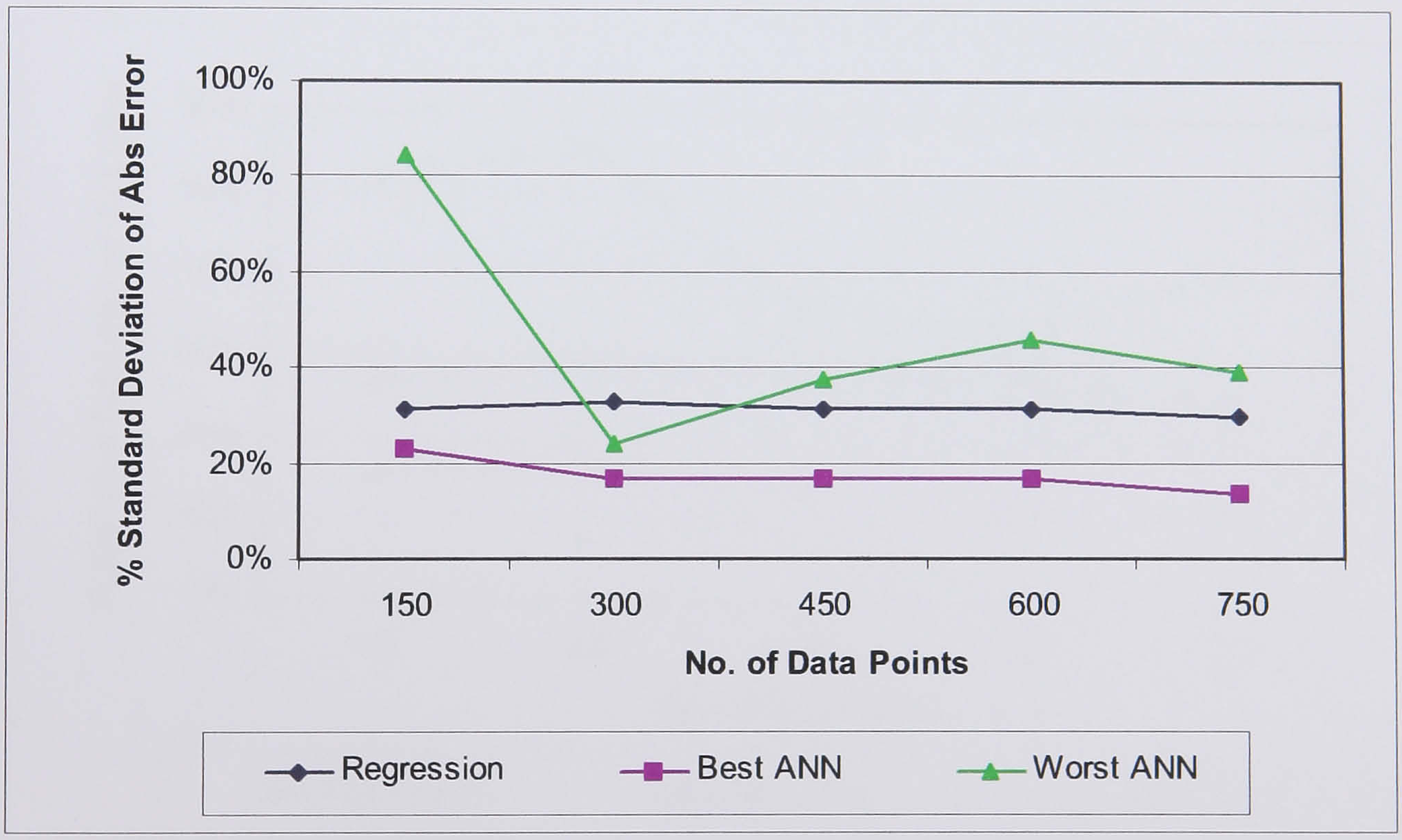

Figure 5.28 Std Dev of Accuracy Vs Number of Data Points – 1 Variable

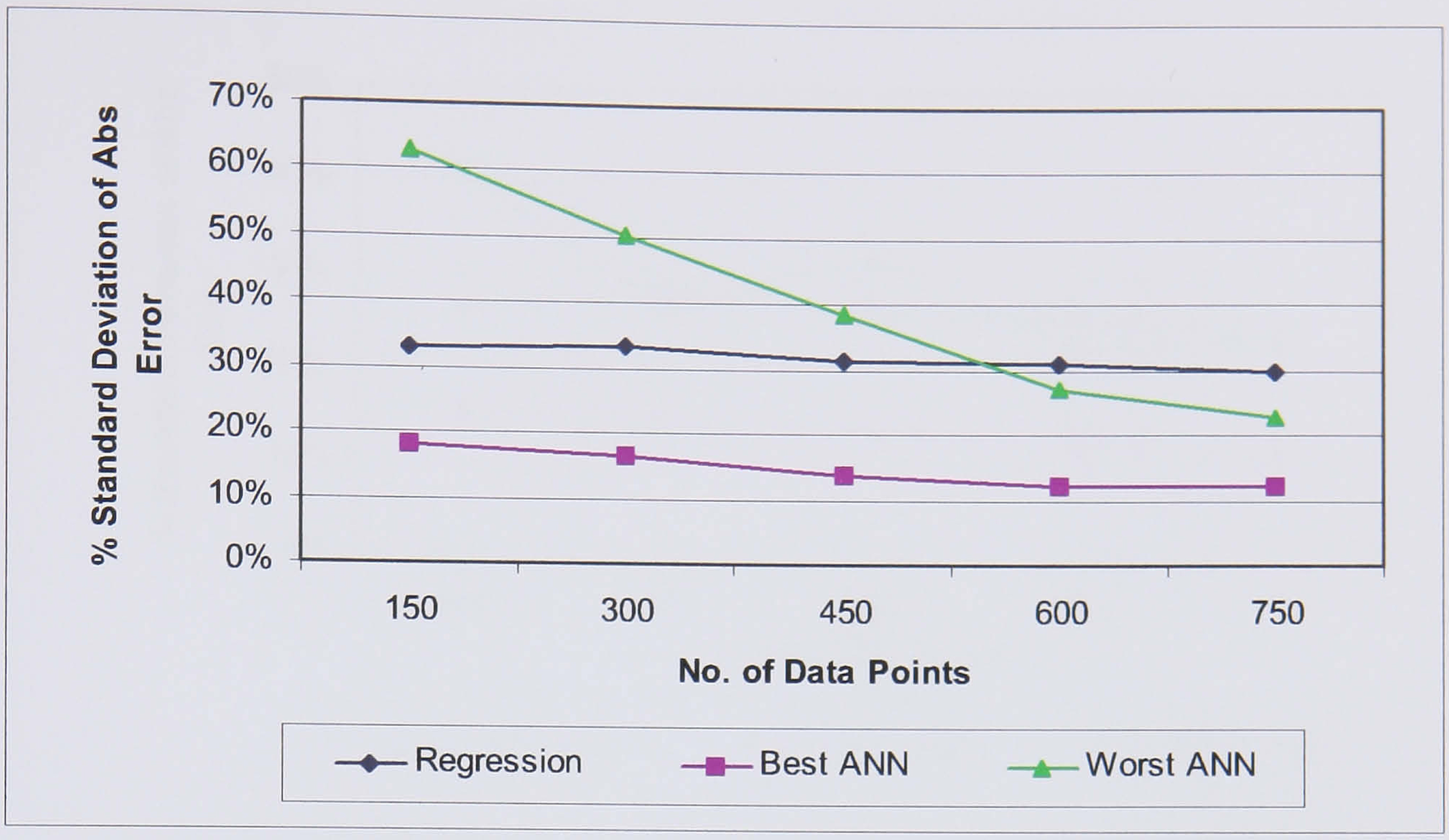

Figure 5.29 Std Dev of Accuracy Vs Number of Data Points – 2 Variables

Figure 5.30 Std Dev of Accuracy Vs Number of Data Points – 4 Variables

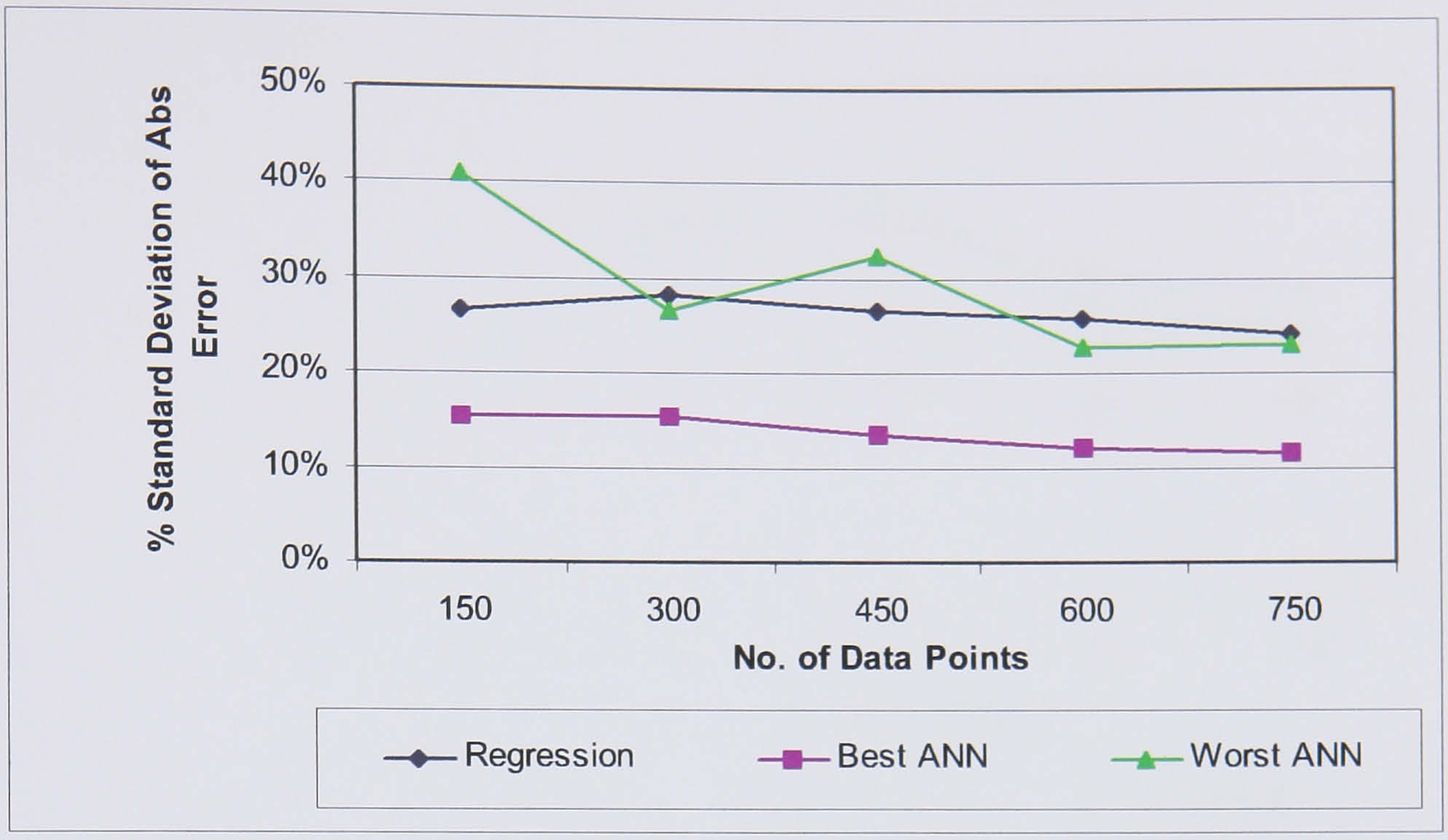

Figure 5.31 Std Dev of Accuracy Vs Number of Data Points – 6 Variables

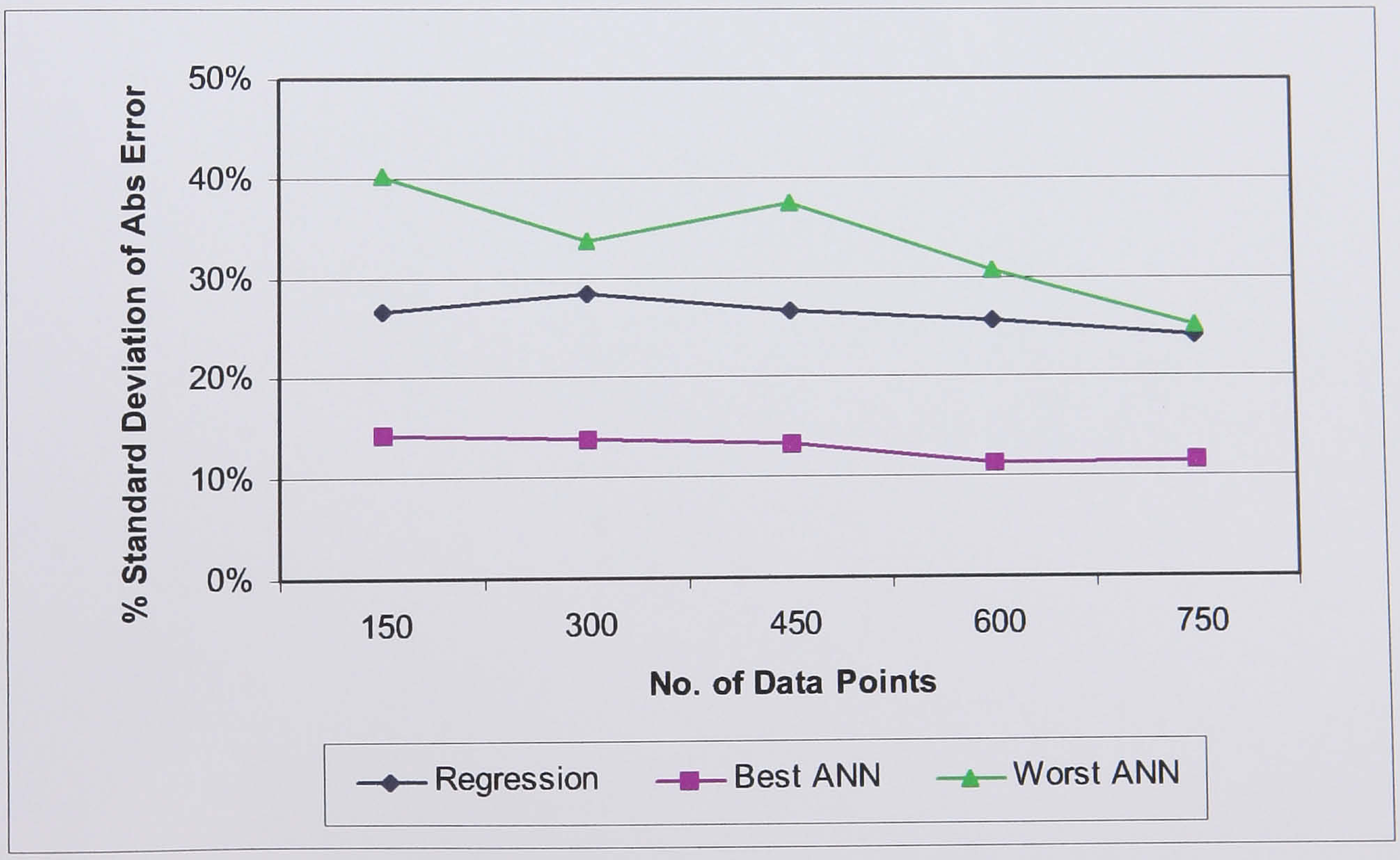

Figure 5.32 Std Dev of Accuracy Vs Number of Data Points – 9 Variables

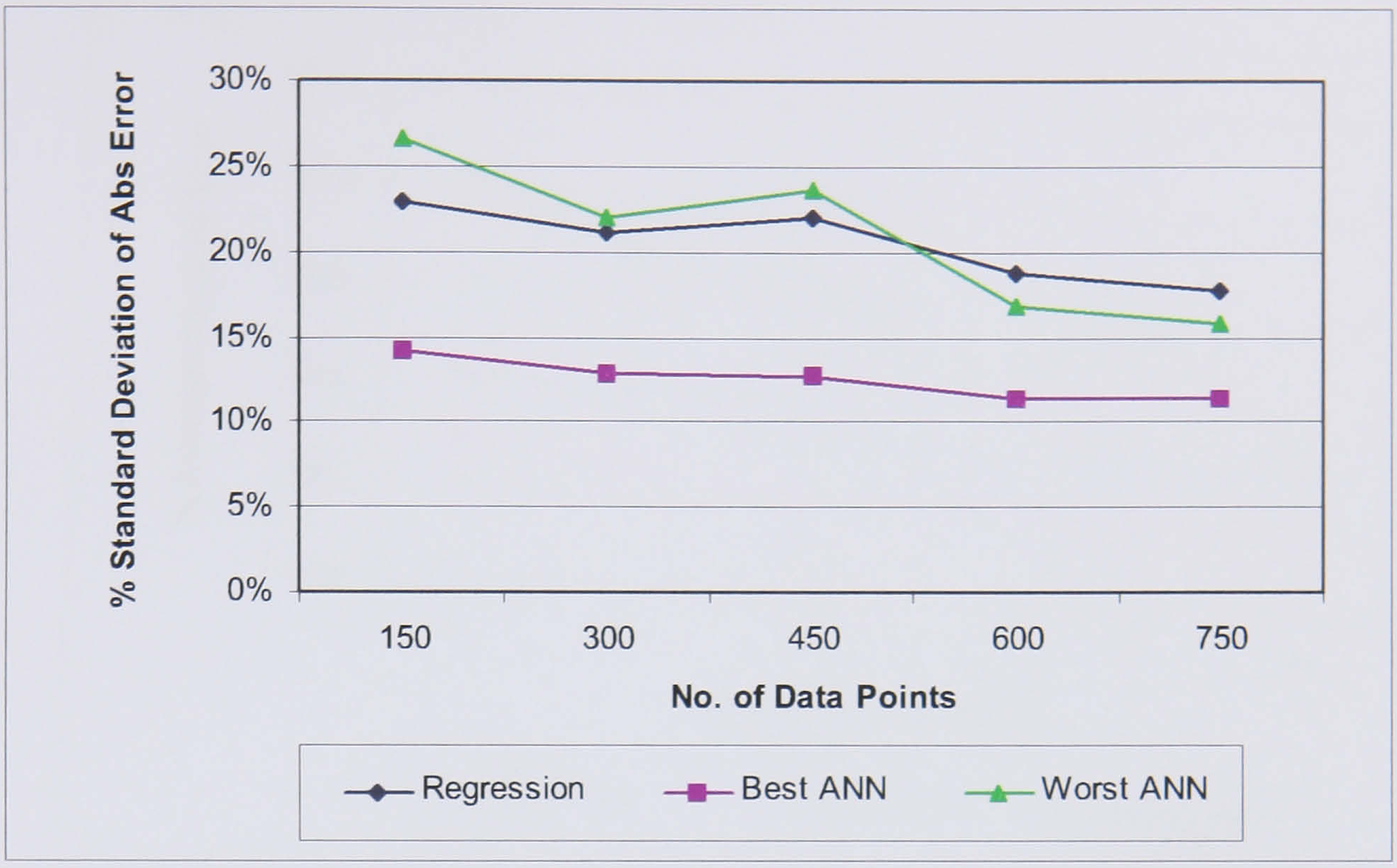

Figure 5.33 Std Dev of Accuracy Vs Number of Data Points – 16 Variables

5.4.2 Estimating Accuracy Vs Number of Variables

Figures 5.34 to 5.38 show the effect on the % average absolute error of varying the number of variables used to construct models. Whilst Figures 5.39 to 5.43 show the effect on the standard deviation in % average absolute errors.

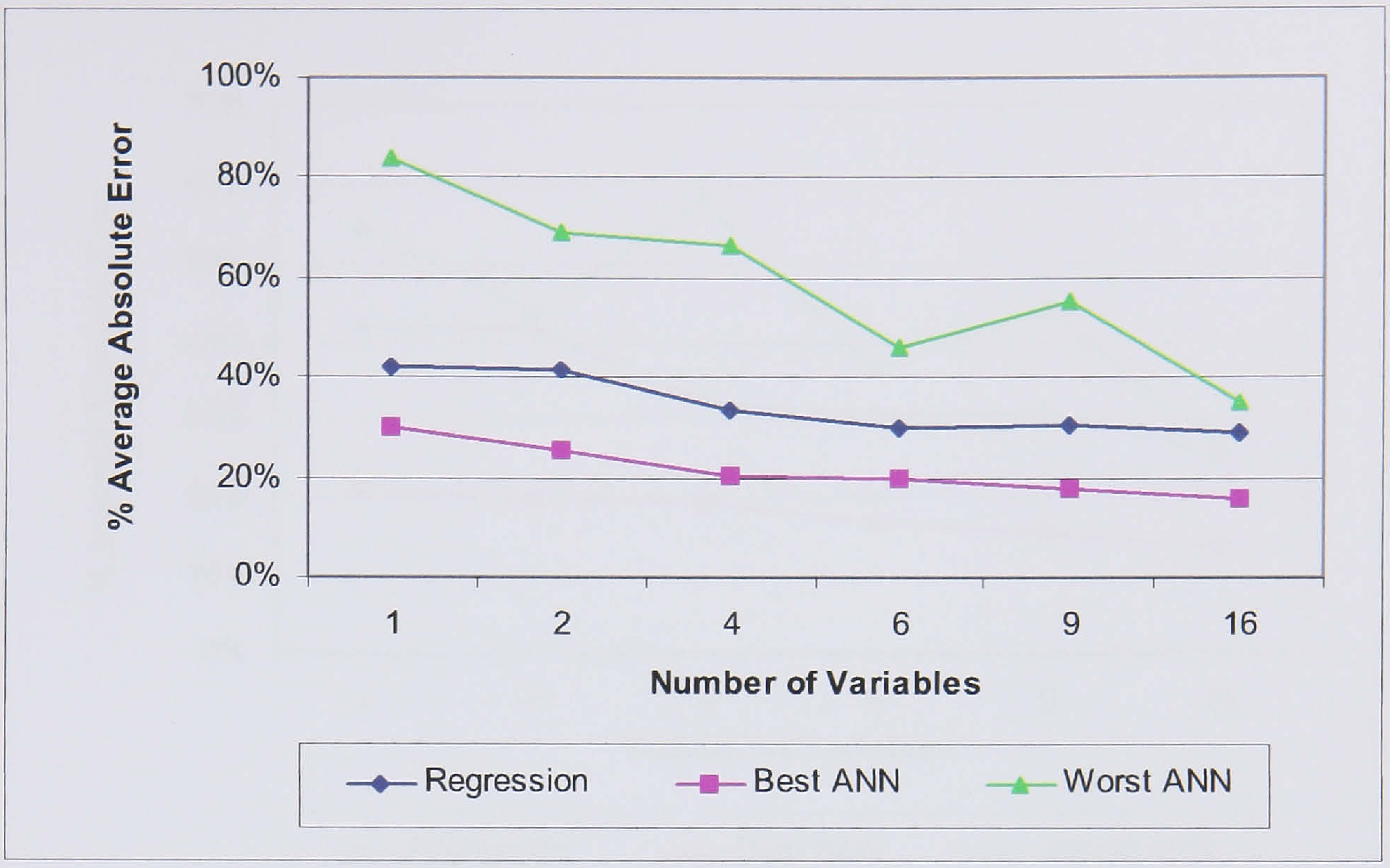

Figure 5.34 Average Accuracy Vs Number of Variables – 150 Data Points

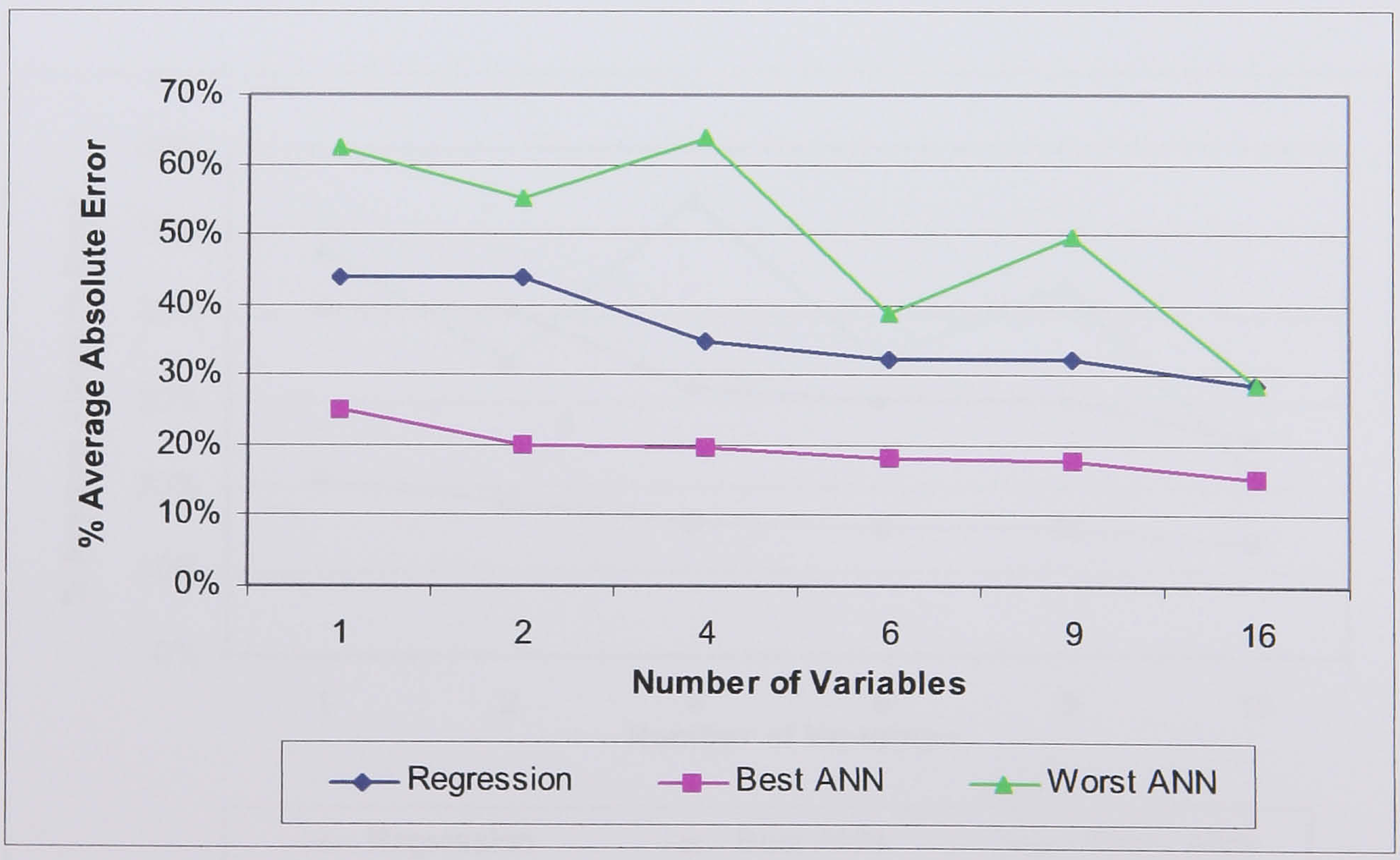

Figure 5.35 Average Accuracy Vs Number of Variables – 300 Data Points

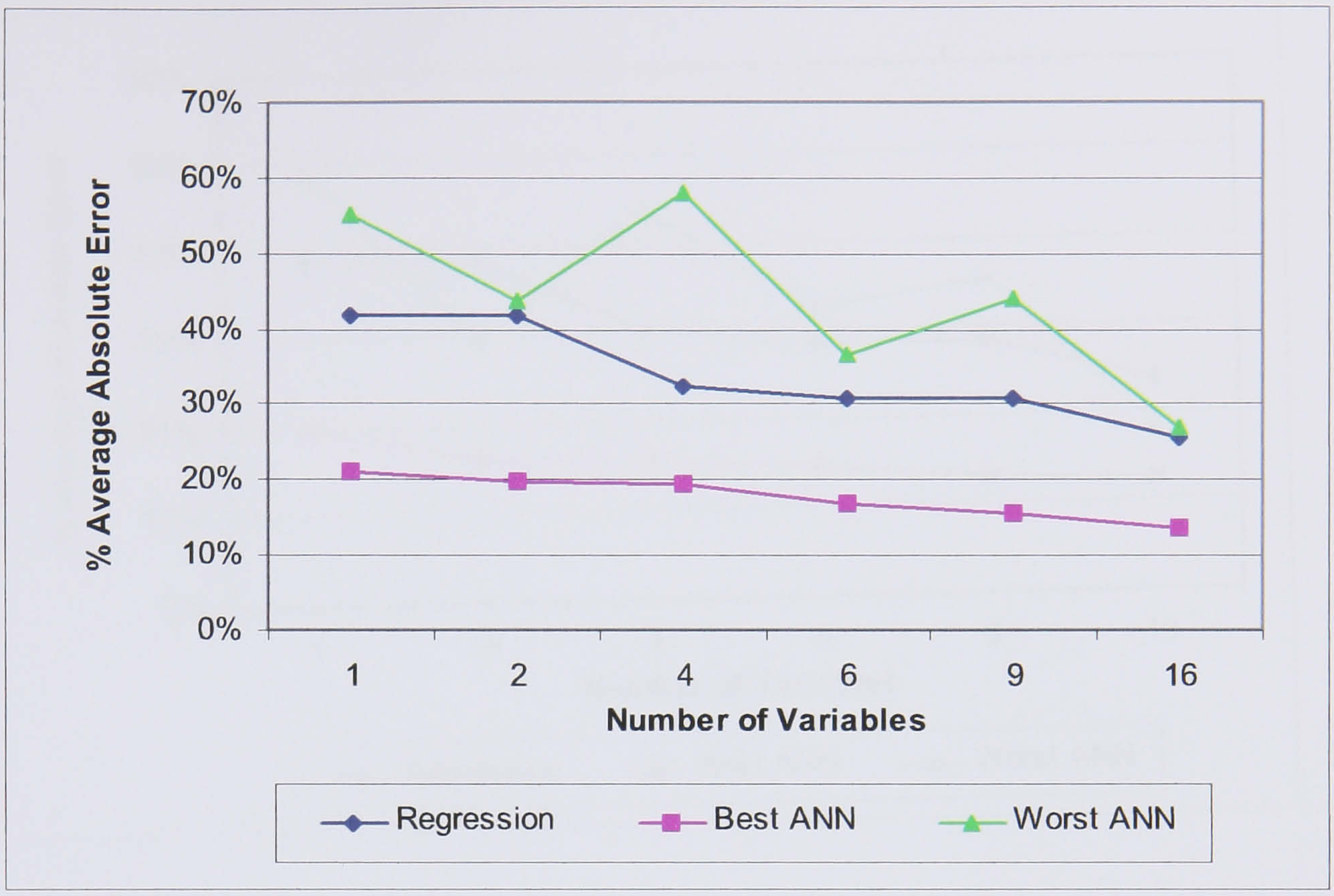

Figure 5.36 Average Accuracy Vs Number of Variables – 450 Data Points

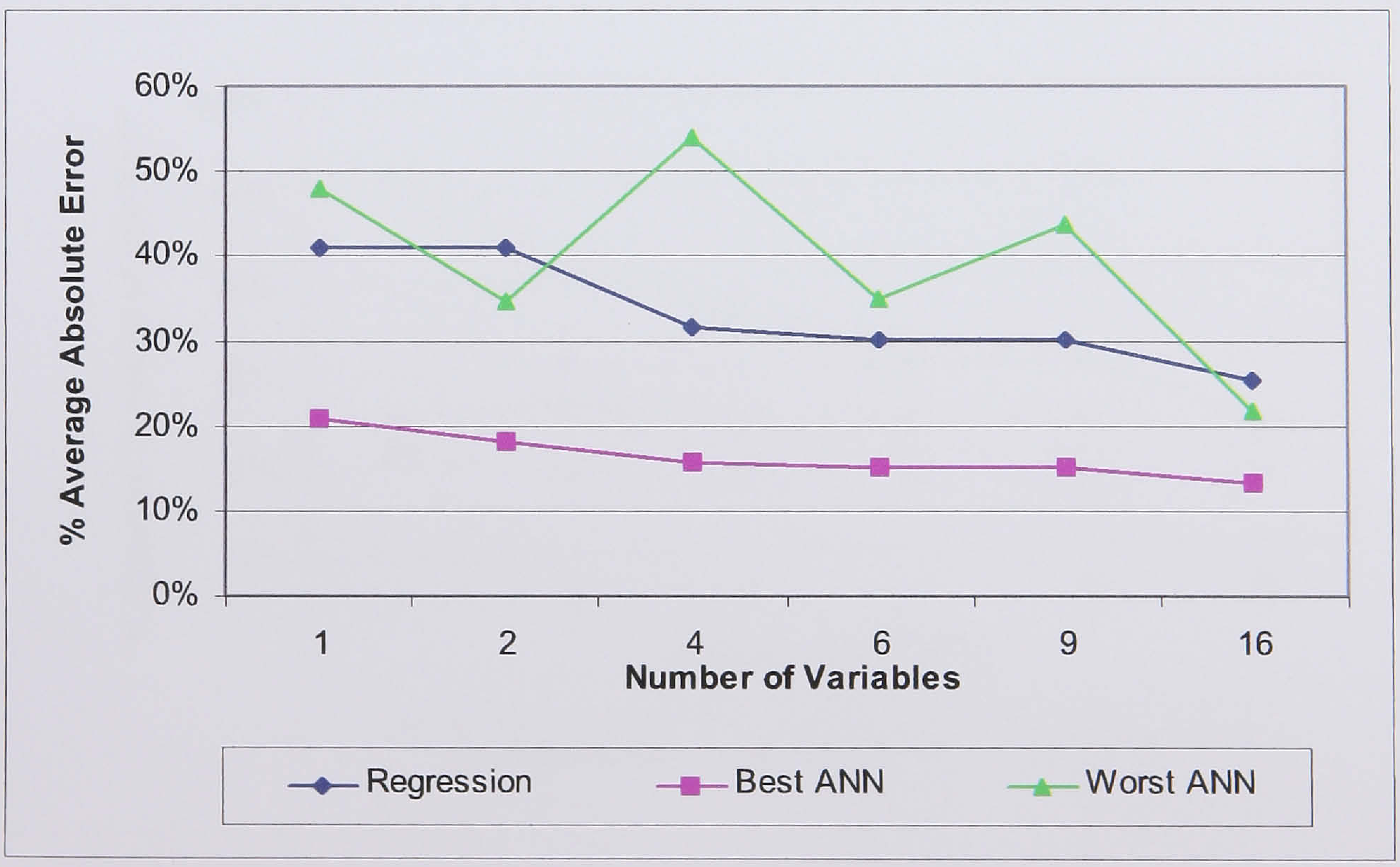

Figure 5.37 Average Accuracy Vs Number of Variables – 600 Data Points

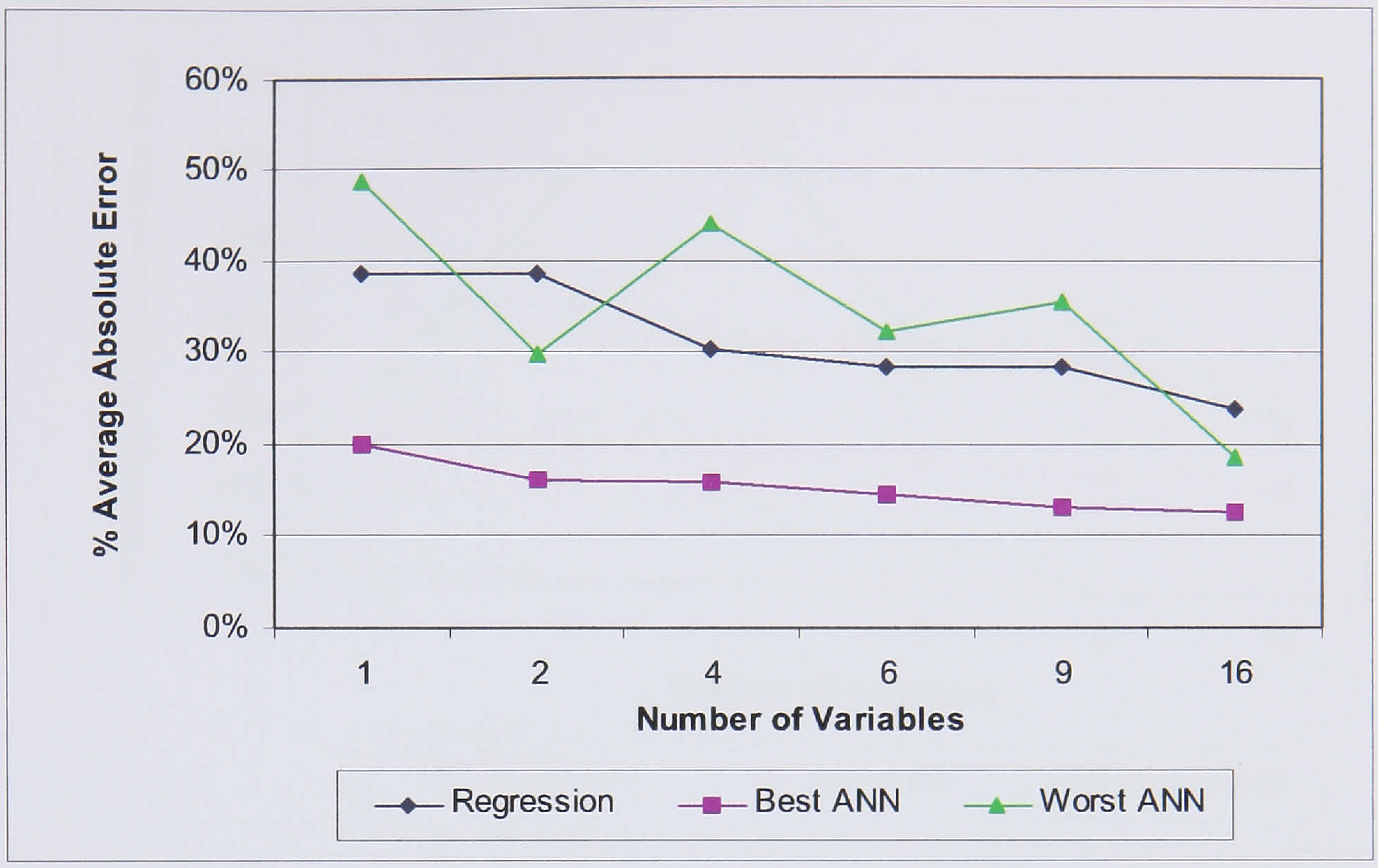

Figure 5.38 Average Accuracy Vs Number of Variables – 750 Data Points

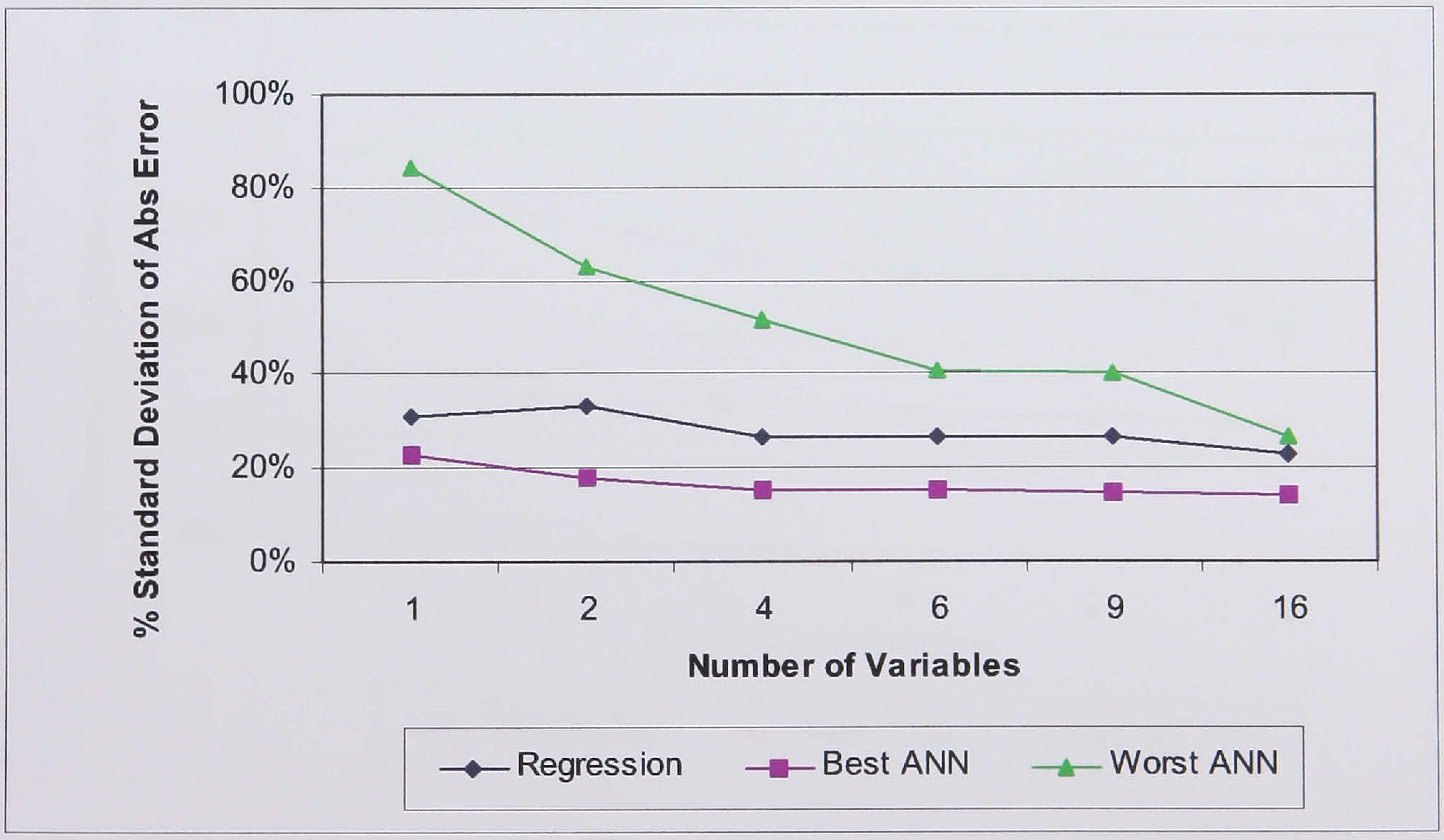

Figure 5.39 Std Dev Accuracy Vs Number of Variables – 150 Data Points

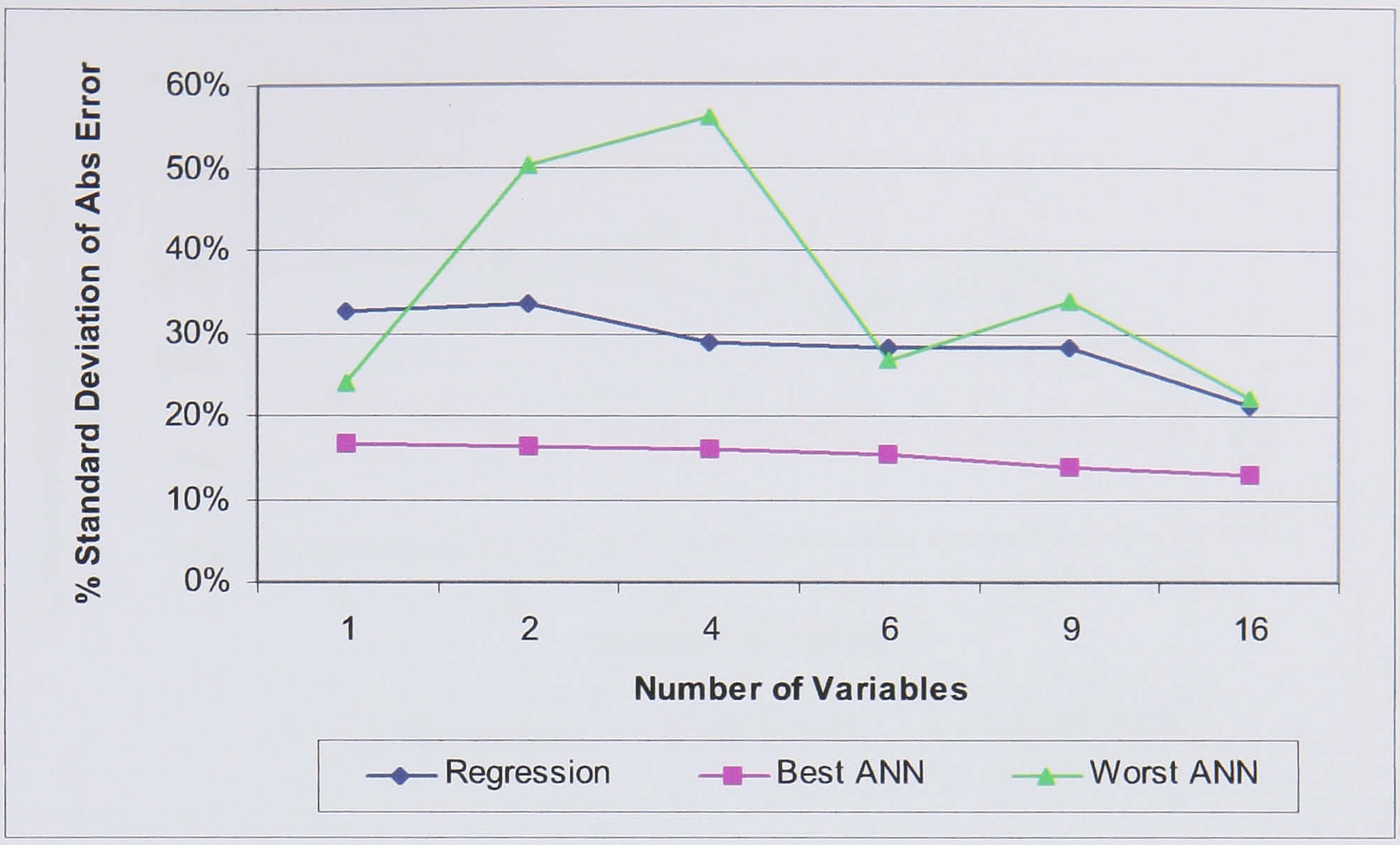

Figure 5.40 Std Dev Accuracy Vs Number of Variables – 300 Data Points

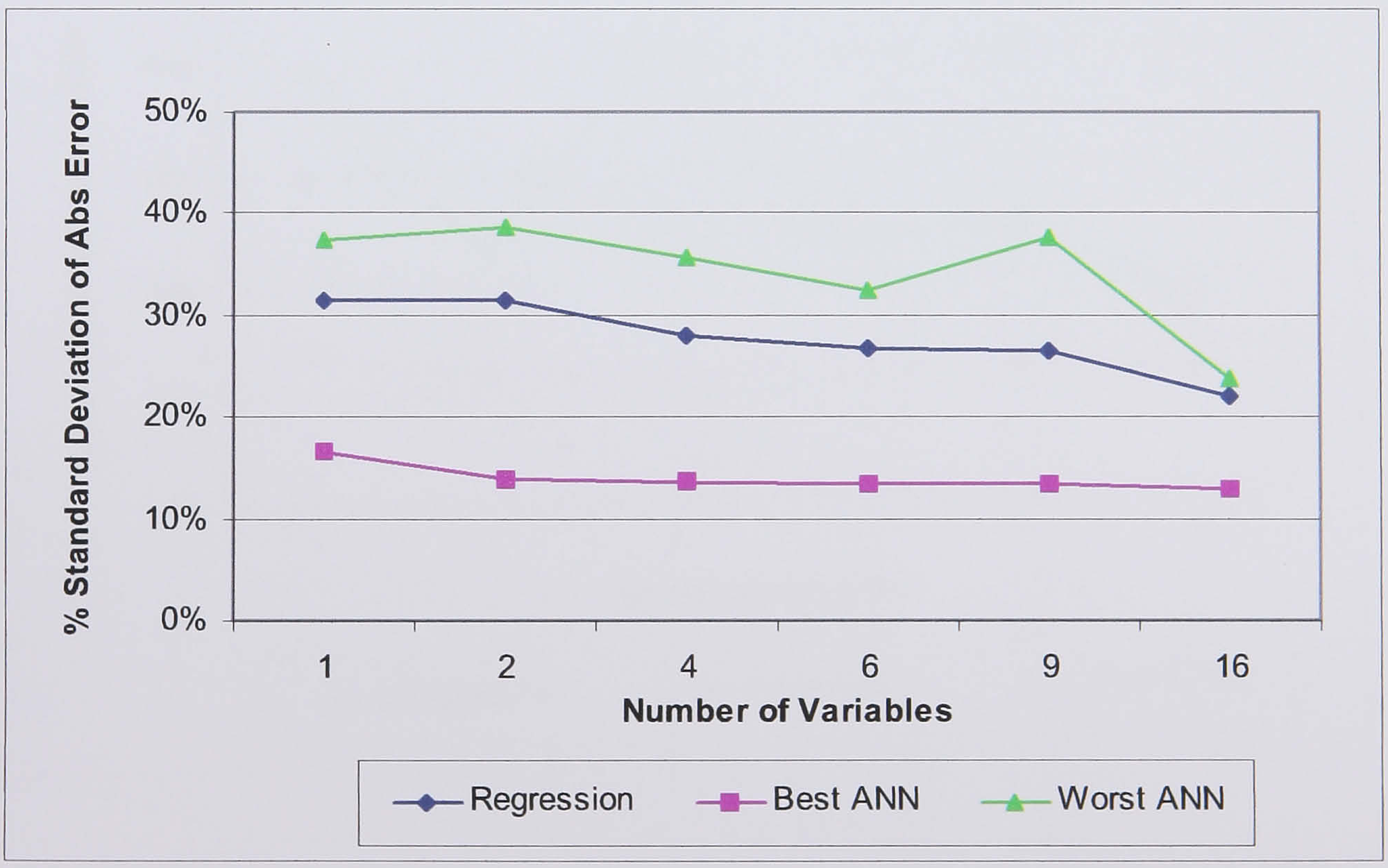

Figure 5.41 Std Dev Accuracy Vs Number of Variables – 450 Data Points

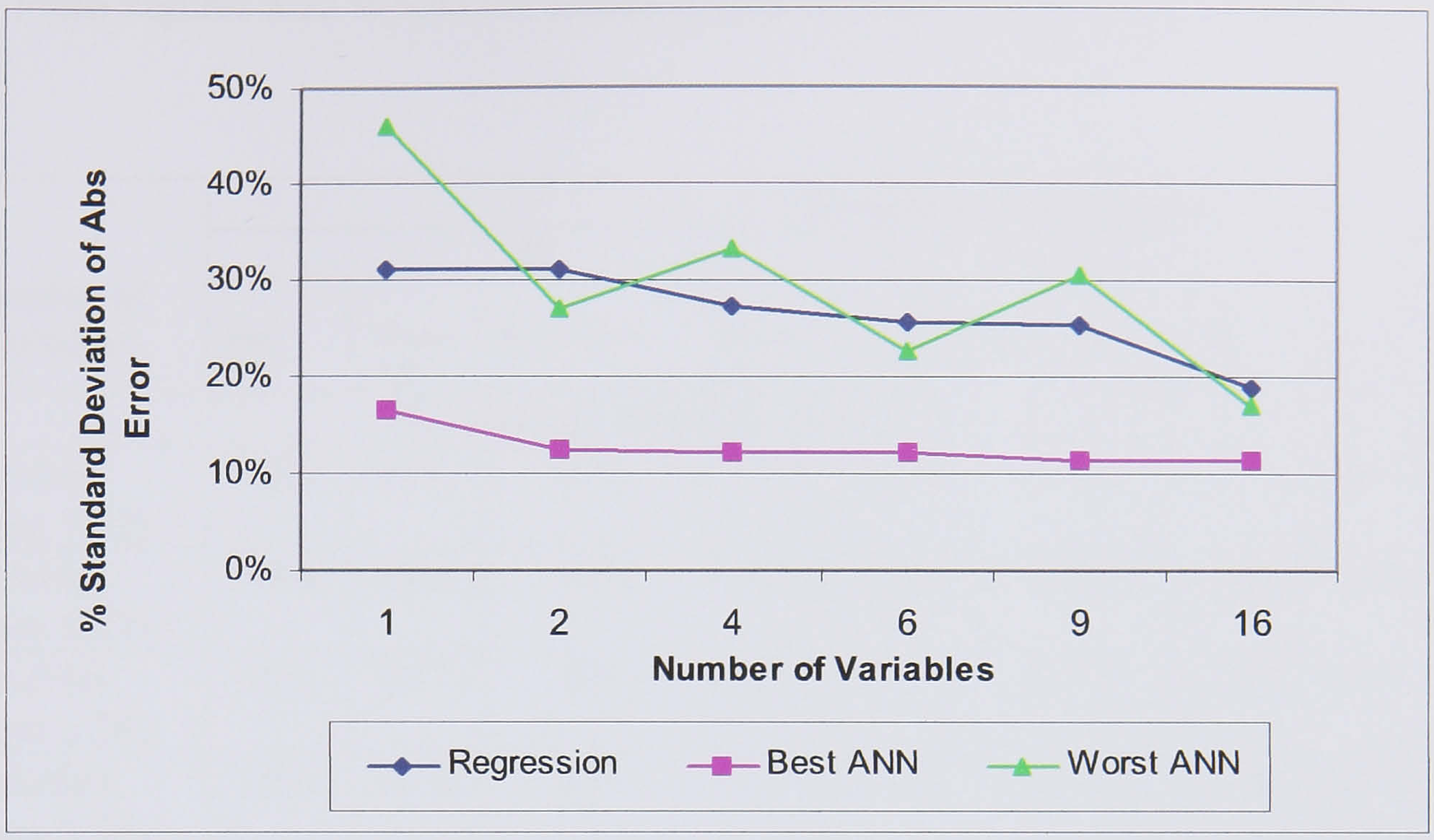

Figure 5.42 Std Dev Accuracy Vs Number of Variables – 600 Data Points

Figure 5.43 Std Dev Accuracy Vs Number of Variables – 750 Data Points

From Figures 5.22 to 5.43 the results shown in Table 5.3 have been extracted.

Number of Variables	Number of Data Points								
	150			450			750		
	Best NN	Worst NN	Regression	Best NN	Worst NN	Regression	Best NN	Worst NN	Regression
% Average Absolute Error									
1 variable (Figure 5.22)	30%	84%	42%	21%	55%	42%	20%	49%	39%
2 variables (Figure 5.23)	25%	69%	42%	20%	44%	42%	16%	30%	39%
4 variables (Figure 5.24)	20%	34%	66%	20%	58%	33%	16%	44%	30%
6 variables (Figure 5.25)	20%	46%	30%	17%	37%	31%	15%	32%	29%
9 variables (Figure 5.26)	18%	55%	30%	15%	44%	31%	13%	36%	29%
16 variables (Figure 5.27)	16%	35%	29%	14%	27%	26%	13%	19%	24%
Standard Deviation of % Average Absolute Error									
1 variable (Figure 5.28)	23%	84%	31%	17%	37%	31%	14%	39%	30%
2 variables (Figure 5.29)	18%	63%	33%	14%	39%	31%	12%	23%	30%
4 variables (Figure 5.30)	15%	52%	27%	14%	36%	28%	12%	41%	26%
6 variables (Figure 5.31)	15%	41%	27%	13%	32%	27%	11%	23%	24%
9 variables (Figure 5.32)	14%	40%	27%	13%	38%	27%	11%	25%	24%
16 variables (Figure 5.33)	14%	27%	23%	13%	24%	22%	11%	16%	18%

Table 5.3 Accuracy Vs Number of Data Points & No. of Variables

From Table 5.3 the following effects can be observed, i.e.:

1. Increasing the number of variables increases the estimating accuracy of the resulting models both in terms of the *% Average Absolute Error* and the *Standard Deviation of % Average Absolute Error.* This effect becomes more pronounced as

the number of data points used to construct the model decreases. However, both increasing numbers of variables and increasing numbers of data points lead to improvements in estimating accuracy. The trends in estimating accuracy shown in Figures 5.22 to 5.43 support this observation.

2. The estimating accuracy of the regression based models, in general increases with increasing numbers of variables but there appears to be no marked increase when the number of data points used to construct models increases.

3. In all cases the estimating accuracy obtained when using the 'worst' network structure is poor when compared with that of the 'best' structure and in many cases the regression models. In addition, the ability of such models to estimate accurate costs is erratic, i.e. in many cases there is no relationship between estimating accuracy, number of variables and number of data points.

4. The greater the number of variables used, the less will be the effect on estimating accuracy of increasing the number of data points.

5.5 Identification of Cost Drivers

Experiments were carried out in order to identify the relative effect on % Average Absolute Error of the individual variables within the turning and drilling models, i.e. to identify those that are the main cost drivers. The results of these experiments are provided in Figures 5.44 and 5.45.

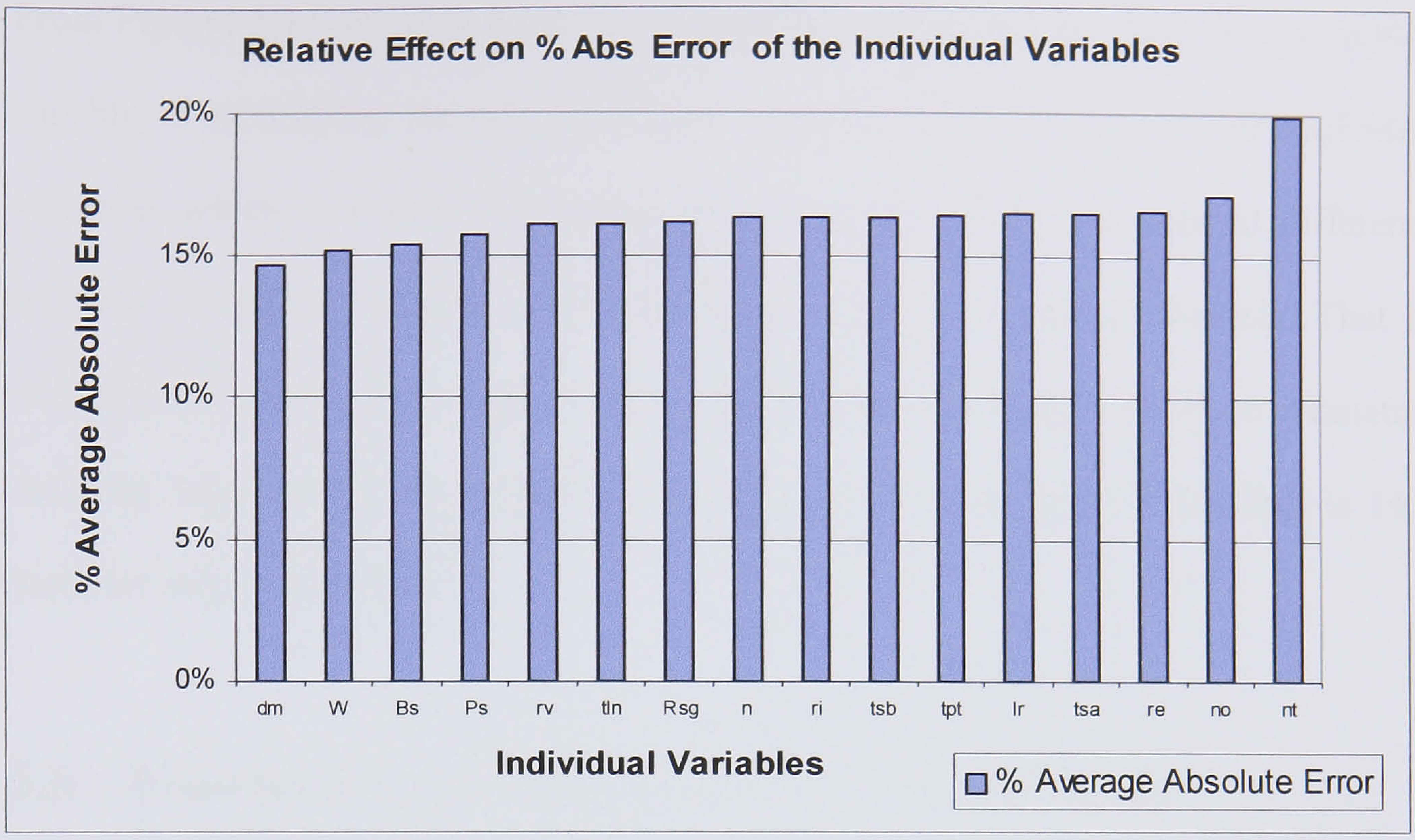

Figure 5.44 Relative Effect of Individual Variables within the Turning Model

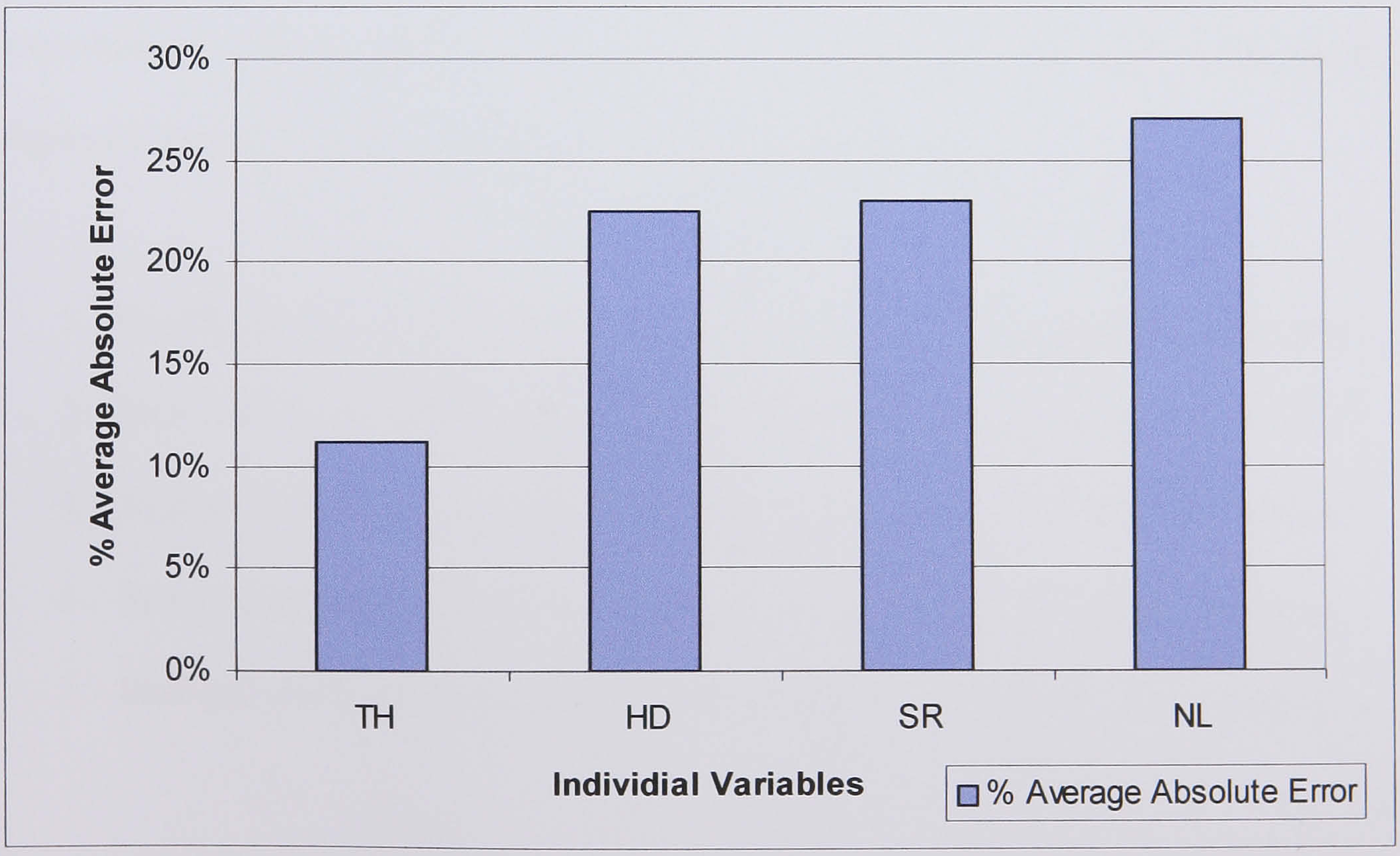

Figure 5.45 Relative Effect of Individual Variables within the Drilling Model

From Figures 5.44 and 5.45 it can be seen that the artificial neural network approach is capable of identifying the relative effects, on estimating accuracy, of the individual variables within a model. The results also show that there is a marked difference between the relative effects of the individual variables within the models. That is, within the turning model there is a 5.5% difference in the relative effect on estimating accuracy between the 16 variables and within the drilling model this effect is 16% between only 4 variables.

5.6 Comparison of Drilling and Turning Models

In order to compare the potential for developing a 'robust' artificial neural network structure, (that is a structure that could be used for a range of costing applications), experiments were carried out for which the results are shown in Figure 5.46, i.e. this figure contains % average absolute errors for the following:

1. Drilling and turning regression models tested using their appropriate test sets
2. Best and worst turning model structures tested using the turning test data set
3. Best and worst turning model structures tested using the drilling test data set
4. Best and worst drilling model structures tested using the drilling test data set
5. Best and worst drilling model structures tested using the turning test data set

Results from Figure 5.46 have been displayed in Table 5.4 for ease of analysis. This table indicates the 'robustness' of the best ANN structure that was developed for the turning application, i.e. this was tested using both the turning and drilling data test sets.

In both cases the level of estimating accuracy was similar which tends to indicate that this model structure could be used within both applications.

However, when the 'robustness' of the best drilling ANN structure was tested this resulted in widely differing estimating accuracy between the two applications, i.e. 26% for turning and 15% for drilling. Although not a conclusive test, the results do tend to indicate that some artificial neural network structures would be more robust than others.

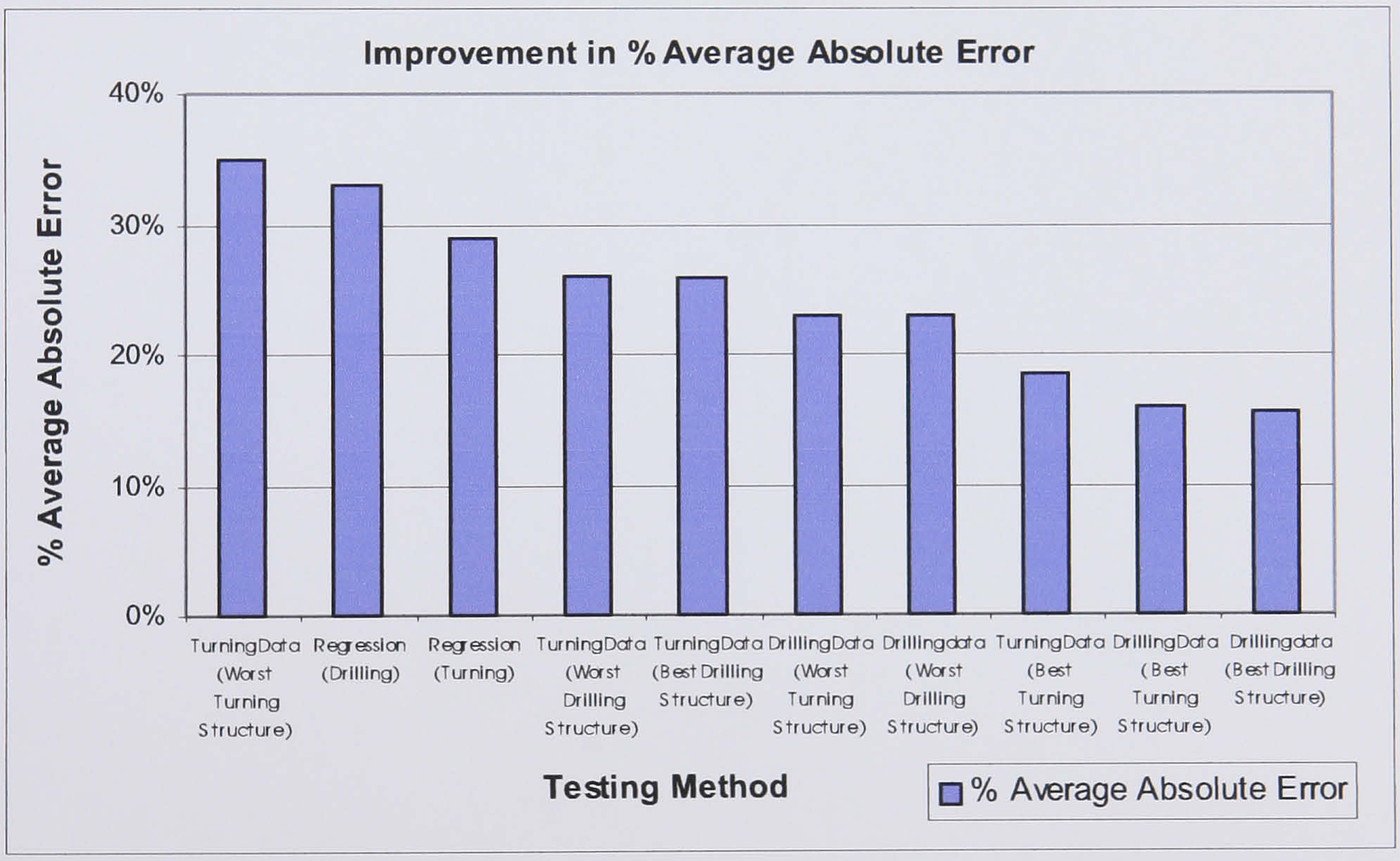

Figure 5.46 Comparison of ANN Model Robustness

	% Average Absolute Error Values			
	Turning Structures		Drilling Structures	
	Turning Test Set	Drilling Test Set	Turning Test Set	Drilling Test Set
Best	18	16	26	15
Worst	35	22	26	22
Regression	29		33	

Table 5.4 Analysis of ANN Model Robustness

Chapter 6 Discussion

6.1 Importance of Cost Models

The primary changes occurring in the global marketing environment are the need for a great choice of products, greater amounts of product customisation, greater choice of manufacturing processes, reduced product development cycles and increased emphasis on minimising total life cycle costs. To remain competitive manufacturing industry must greatly increase the number of product variants available to these markets. This will require manufacturing industry to both develop and make use of a wider range of materials and manufacturing processes.

In order to support these changes it is expected that the demands on the cost estimating function will greatly increase. However, a review of the research literature has identified that limitations exist when using the current cost estimating process to generate cost information. The main limitation is that cost estimating is a highly skilled, complex process that according to Ostwald (1988), Cunningham and Dixon (1988), and Chang (1990) requires its practitioners to possess a high level of expertise. Sufficient expertise is required to enable determination of the purpose, scope, and time constraints for developing the estimate, analysis of the details of the work to be done, and identification of the types and quantities of materials, parts and equipment required. These tasks are both labour and time intensive and make the cost estimating process not only costly but also unresponsive to many of the costing needs of such functions as product and process development. In addition, each time a new estimate needs to be developed or updated the majority of the cost estimating tasks formally employed must normally be repeated. A comparison, Table 2.4, of several representative techniques for establishing process times indicates that there is a deficiency in their ability to cope with the changes occurring in the manufacturing environment that are listed in Table 1.1.

To offset these limitations, the use of cost models are now becoming an essential tool within the cost estimating process since there are significant gains to be made in terms of the lower set-up and operating costs, higher quality of estimates and increased responsiveness to demands for cost information. The cost modelling process makes use of cost estimating tasks but with differing objectives, i.e. the primary objective is to collect appropriate cost, product and process data such that the basic relationships can be established, between costs and the product and/or process variables that drive these costs. Once these relationships have been established, normally in the form of mathematical equations, users need merely to input appropriate values of product and/or process variables and the cost model then outputs the relevant costs. Hence, the need to repeat costly and time intensive cost estimating tasks is avoided.

Because of these benefits, there have been a wide variety of applications for cost models in the manufacturing domain with recent applications focussed on assisting:

a. product development, e.g. identifying low cost design, supporting a concurrent engineering environment and supporting design for manufacture,

b. process development,

c. the determination of process capacity,

d. machine time determination and job costing,

e. miscellaneous tasks such as process planning, forecasting capital investment, producing component routings, and

f. estimation of life cycle costs.

6.2 Cost Modelling Methods

In order to support the cost estimating process, it is expected that the quantity, type, accuracy and complexity of cost models will need to be greatly increased. Hence, there is an increasing need to ensure that the process of developing cost models remains both responsive to user needs and effective in terms of the resources required for developing models. Existing cost modelling tools and techniques must, therefore, be able to cope with the greater number of cost models required, generate cost models using less historical cost data, require less time to develop models, model greater levels of process complexity and require less input from process experts. In this respect, of particular importance are the mathematical modelling techniques used to establish the 'cost estimating relationships' (CERs) which form the basis of cost models. These tools must not only enable appropriate CERs with an acceptable level of estimating accuracy to be developed but must also enable these cost models to be developed without detrimental effects to the overall cost model development process, i.e. in terms of excessive amounts of time or costs being incurred.

A variety of techniques have been employed to identify cost estimating relationships of which *regression analysis* is the most widely used. There are also a variety of regression based techniques of which *multiple linear regression* is the commonest in use. Non-linear regression techniques are also available but dependent on the user pre-specifying the type of non-linear relationship that exists. This requires knowledge of both the cost application area being studied and the methods involved in the application of regression analysis. A main limitation of using regression methods is that these techniques quickly become ineffective as the number of predictor variables within a model increases, hence the technique may not be able to cope with the increasing complexity of future manufacturing products and processes. In addition, the regression technique cannot distinguish between a natural causal relationship between variables and one occurring by chance. Hence, process and product expertise is essential in order to choose the predictor variables with care.

6.3 Application of Artificial Neural Networks to Cost Modelling

From its initial development in the early 1940's (McCulloch and Pitts, 1943) ANN technology has advanced tremendously in terms of its ability to identify complex relationships. Current artificial neural network structures are made up of three basic types of layer, i.e.

a. the input layer which accepts information from external sources and assigns weighted values to these depending on their relative importance as cost drivers,
b. the hidden layer which processes this input information and converts it to the required output data, and

c. the output layer which outputs cost data from the artificial neural network.

Each layer contains processing elements the number of which in any one layer can be varied as can the number of hidden layers within any one network. As values for process variables are input into the artificial neural network, the processing elements within the input, hidden and output layers are modified such that the difference between the output cost values and actual cost values, i.e. the error, is gradually minimised. This process, termed ' training the network' is performed within the current research work using 'back-propagation', i.e. this technique calculates an error between actual values and output values and propagates the error information back through the network to each processing element in each layer. This back-propagated error then drives the learning at each processing element.

Recently, artificial neural networks have generated much research interest in the manufacturing area although many of the applications reported in the literature are either laboratory experiments or preliminary applications. Lippmann, (1987) identified several potential advantages, when compared to conventional methods, of using artificial neural networks, i.e.:

a. they require less assumptions to be made concerning the shapes of underlying distributions than traditional statistical methods,
b. they can easily run on parallel processors due to the inherent parallelism of their architecture, hence computing time is shortened, and

c. they provide a high degree of robustness or fault tolerance because they are composed of many processing nodes, and hence damage to a few nodes or links need not significantly impair the overall performance.

Early attempts to embed artificial neural networks techniques within the cost estimation area include Shtub and Zimerman (1993) who developed models for estimating the cost of assembly systems. Performance evaluation and a systematic comparison with conventional methods was, however, not undertaken by these researchers.

König (1995) compared the estimation quality of artificial neural networks with that of conventional linear and non-linear regression analysis. In general, artificial neural networks estimated costs with higher levels of accuracy than conventional regression methods. However, these results were based on a small number of test data and thus could be prone to statistical errors.

In common with conventional statistical methods, particularly regression analysis, Haykin (1994) identified essential characteristics of ANNs that indicated their validity as cost modelling techniques, i.e. the ability to learn, adaptivity to a variety of costing situations, and ability to model non-linear relationships. Bode (1998) developed ANN based cost models that could successfully deal with a wide range of variety within a specific costing application. Bode (2000) also concluded that artificial neural networks produce better cost predictions than conventional costing methods only if a sufficient cost case base is available and the cost-driving attributes are known prior to the start of modelling.

Previous work (Stockton and Wang, 1999) outlined how artificial neural networks could potentially provide a suitable method for overcoming some of the constraints to the development of cost models. There has been no rigorous attempt, prior to the research reported in this thesis, to examine the application of artificial neural networks to the cost modelling process.

6.4 Influence of ANN Structure

A central theme highlighted by the research literature is that of the difficulties involved in the selection of the most appropriate artificial neural network structure for individual applications, i.e.

a. Udo (1992), and Looi (1992) identified the lack of a generalised network for solving different types of problems.

b. Arizono et al (1992) concluded that a significant problem was the question of reasonably specifying the values of parameters and weights included in the network model.

c. Li et al (1994) identified that, when attempting to use ANNs, the prime difficulties faced were the selection of the optimal number of neurons in the hidden layer.

d. Luong and Spedding (1995) identified that no unified or formulated procedures existed for designing appropriate networks and concluded that network design is still very much a black art.

e. Additional factors found to influence the effectiveness of an ANN and where decisions are often taken based on trial and error include deciding; the network topology; the network parameters such as learning rate and momentum factor; the maximum and minimum value of weights; the number of examples in a training set; whether the nature of the examples in a training set encompasses the diversity of a problem; the extent to which the examples are learned; the type of learning method used.

In the main only general statements concerning the selection of ANN structural elements are provided by the research literature. For example, according to Geman et al. (1992) the normal understanding is that the generalisation ability of a network will increase as the number of hidden nodes increases. In addition, networks may not learn properly if there are too few hidden nodes, whereas too many nodes would generate redundant nodes to deteriorate the performance of the network. Overtraining is also reputed to reduce the 'generalisation' ability of a network (Martinez et al., 1994).

6.4.1 Structure of Processing Elements

The processing element forms the heart of the artificial neural network and it is the functions associated with these elements that provide the artificial neural network with the ability to model a wide variety of relationships between input and output variables.

Processing elements (PEs) contain a number of mathematical functions as shown in Figure 3.3. These functions act in a sequential manner to transform input values into output values. Input values can either be externally derived input values of predictor variables or outputs from processing elements in a preceding layer. The functional types examined within the current work were as follows:

i. **Weighted Summation Function** – Sum and Majority
ii. **Transfer Function** - Linear Function, Sigmoid Function, and Sine Function
iii. **Noise Function** – Uniform Noise, Gaussian Noise, and No Noise
iv. **Output Function** - Direct, Select and One-Highest
v. **Error Function** - Standard , Quadratic, and Cubic
vi. **Learning Rules** - Hebb Rule, Perceptron Rule, and Delta Rule

6.5 Effect of Artificial Neural Networks on Cost Modelling

Previous research has focussed on the use of 'estimating accuracy' to determine the effectiveness of cost models and of alternative cost modelling techniques. However, the research reported here has taken a broader view and examined both the range of characteristics that are used to describe individual cost models and the individual tasks required in the development of cost models. Hence, the current research investigates how the use of artificial neural network modelling techniques can assist the cost modelling process in relation to identifying the benefits to and the limitations placed on:

i. the individual characteristics of cost models as shown in Figure 2.3.
ii. the tasks involved in the cost model development process as shown in Figure 2.5.

6.5.1 Cost Model Characteristics

From Section 2.3 the basic characteristics of a cost model can be determined, i.e. these are as follows:

a. accuracy of cost estimates provided by the cost model,

b. amount of subjective judgement required to develop and use the cost model,

c. type and expertise of the personnel who can develop and use the cost model,

d. time required to use the model to obtain a process time or cost,

e. level of detail of the input and output data from a cost model,

f. costs of setting-up and operating the cost modelling system, and

g. variety of tasks and products the costs of which can be estimated using a model.

6.5.1.1 Estimating Accuracy

The estimating accuracy of an ANN generated cost model is strongly dependent on the structure of the network as shown by the experimental results presented in Chapter 5. In particular, in order to achieve the highest estimating accuracy it was found necessary to choose, with care, the following network elements, i.e.:

1. **Type of Learning Rules used within processing elements.** Here the ideal type, for the drilling application was found to be the Ext DBD rule and that for the turning application was found to be the Delta rule, i.e. these caused the least amount of estimating error. The fact that the type of learning rule that represented best practice differed depending on the application tends to suggest that there may

be difficulties in identifying a generalised ANN structure that is robust in terms of the range of application areas over which it is applicable. The choice of function type, i.e. the Summation function, having the least effect on accuracy had variations between best and worst function types that equalled 3.2% for turning and 0.05% for drilling. Where high volume or highly repetitive tasks are being carried out 3.2% could represent an unreasonably large amount of error. Hence, depending on the application area and the level at which the cost model is required for use, (i.e. strategic, tactical or operational), all function types within processing elements may need to be carefully selected.

The average effect of PE function types on accuracy was found to be 31.1% for turning and 12.5% for drilling. Although this represents a large difference this appears to have little effect on the overall estimating accuracy of the resulting models, i.e. 18% for turning and 16% for drilling. This effect would tend to favour the use of a generalised ANN structure since the best artificial neural network structure developed for one application could be used in other application areas without an excessive decrease in estimating accuracy. There appears to be no apparent reason for this effect. Potential factors that may account for this effect, however, are the number of variables within the model, (i.e. 16 turning variables and 4 drilling variables), and/or the relative effect of variables on estimating accuracy, (i.e. as shown in Tables 5.44 and 5.45). Further work needs to be carried out to establish where the true cause of this effect lies and its relationship to the robustness of individual artificial neural network structures.

2. **The number of hidden layers within the network.** Overall increasing the number of layers within an artificial neural network tended to lead to a decrease in estimating accuracy. From Figures 5.15 to 5.16 it was identified that this relative decrease in estimating accuracy depended on the number of processing elements per layer.

Figure 5.20 indicates that the accuracy of the 1-layer, 2-layer and 3-layer ANN models converges at 12 PEs per layer. Hence, when the number of PEs per layer is 12 or greater then accuracy is no longer dependent on the number of hidden layers within the ANN structure. The underlying trend in the improvement of estimating accuracy as the number of PEs per layer increases is shown in Figure 6.1.

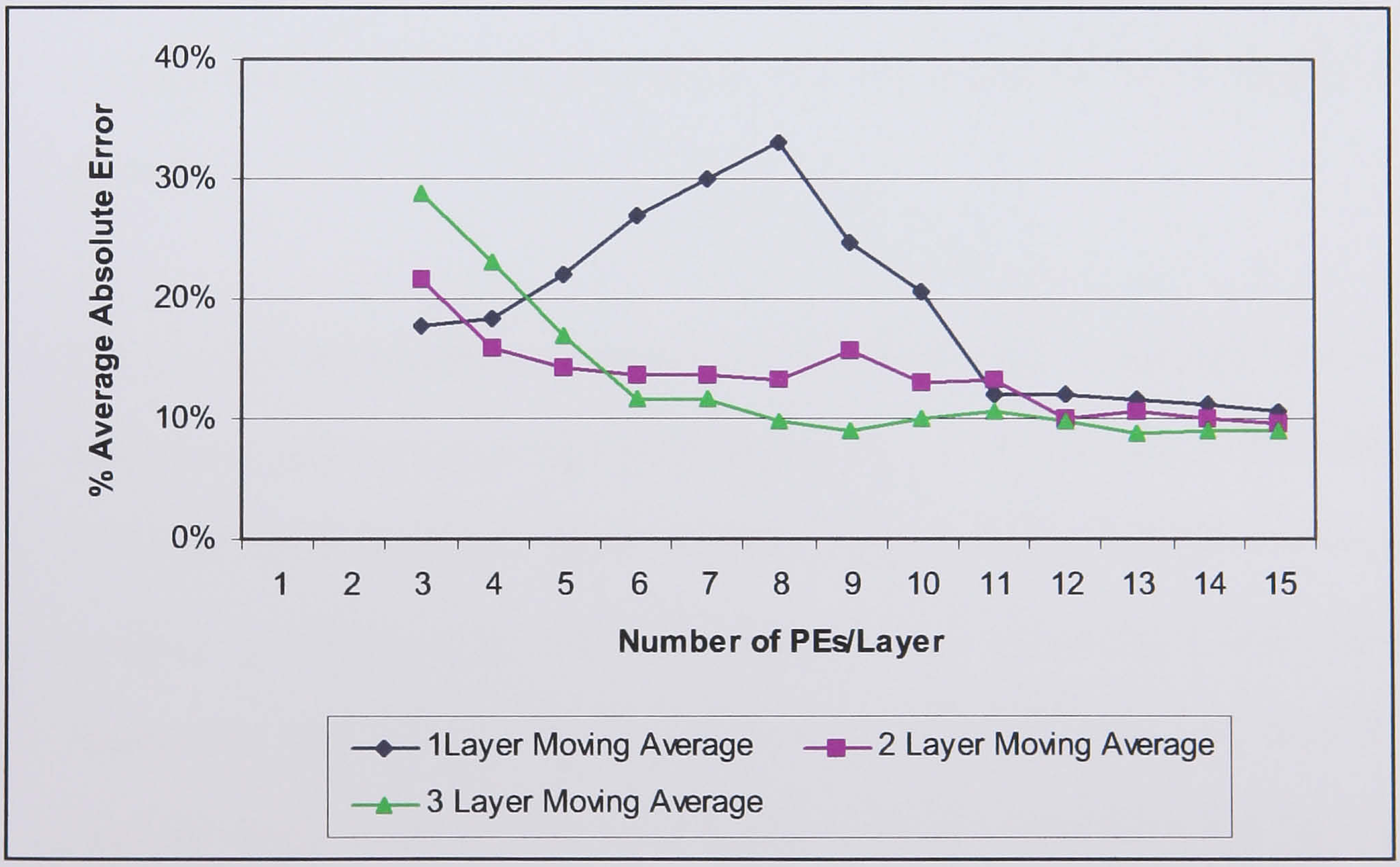

Figure 6.1 Moving Average for 3 Layers

This figure displays the 'moving average' (Stevenson, 1993; Monks, 1995) estimating accuracy values obtained by summing and averaging the individual values from a given number of PEs repetitively, i.e. each time deleting the oldest value and adding the new value. For example, consider the 1-layer model the respective values of estimating accuracy for 1, 2, and 3 PEs are 13%, 18%, and 22% and hence the average is 17% which is obtained by adding these 3 values together and dividing by 3, i.e. the number of values. This is the first value of the 1-layer ANN model to be plotted. The 2^{nd} plotted value is then the average of the ANN models with 2, 3 and 4 PEs, the 3^{rd} plotted value being the average of the ANN models with 3, 4 and 5 PEs and so on until all values have been plotted. Moving averages remove fluctuations in data series whilst preserving the general pattern of the underlying trends. It can be clearly seen from Figure 6.1 that the % Average Absolute Error values converge when the number of PEs is approx. 12 per layer.

3. **The number of processing elements (PEs) per layer.** Where networks contained one hidden layer there is no discernible trend in estimating accuracy as the number of PEs per layer increased. There was also a large variation found in estimating accuracy, i.e. between 12% and 37%. Where networks contain two hidden layers, Figure 5.18, after an initial increase in estimating accuracy from 1 PE/layer to 2 PEs/layer there occurred no further discernible change when additional PEs were introduced. A marked decrease in variability of estimating accuracy was also observed, i.e. between 9% and 20%. Where networks contain three hidden layers, Figure 5.19, again there existed an initial increase in estimating accuracy from 3 PEs/layer to 4 PEs/layer but there after no discernible difference when additional

PEs are introduced. Again a decrease in variability of estimating accuracy was observed, i.e. between 7% and 17%.

Figure 6.2 has been constructed in order to examine the effects on estimating accuracy of the total number of PEs within a model irrespective of the number of PEs per layer. For example, the 3-layer model containing 5PEs per layer contained a total of 15 PEs, (3 layers x 5 PEs per layer). The estimating accuracy obtained using this model, (i.e. 13%) has, therefore, been plotted against the 15 PE value.

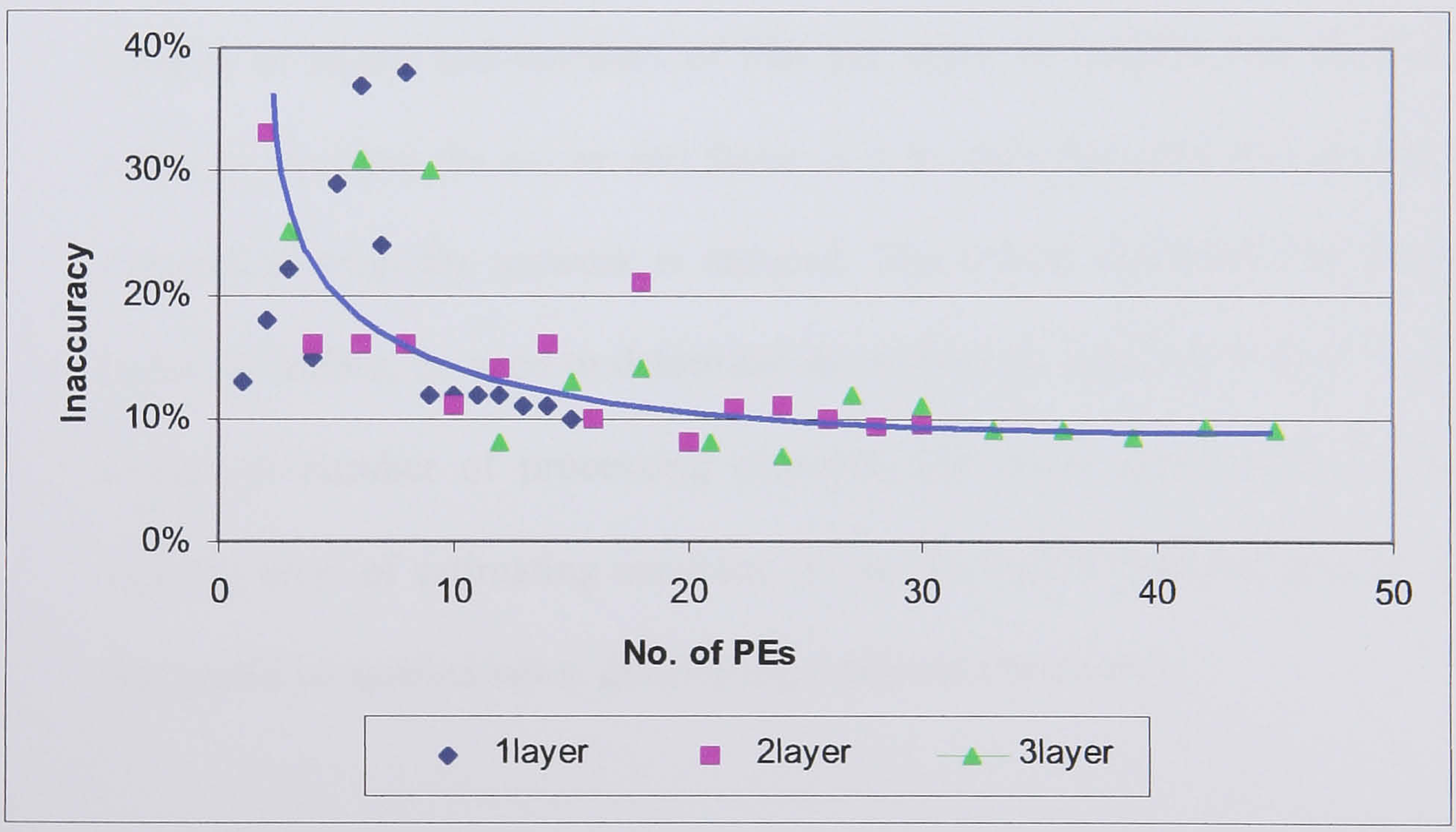

Figure 6.2 Number of PEs Vs Inaccuracy

Figure 6.2 indicates the following:

1. Irrespective of the number of layers within models, increasing the number of PEs leads initially to a sharp increase in estimating accuracy. This

increase in accuracy begins to level out at approximately 16 PEs, and above this value there is no discernible improvement in accuracy.

2. Irrespective of the number of layers within models, increasing the number of PEs also leads to a reduction in the erratic nature of the estimating ability of ANN models. Above 32 PEs per ANN model, there is no further discernible improvement in estimating ability.

When designing artificial neural network structures for a specific application it is important to maintain adequate levels of simplicity, i.e. to minimise the number of layers and numbers of PEs per layer. In general, the simpler the network structure the easier and faster is it to train the network and the data required to train the network is reduced. The results presented in Chapter 5 could, therefore, be used to determine the minimum number of layers and the minimum number of processing elements per layer necessary to obtain a specific level of estimating accuracy. From the results obtained general rules that could be applied when developing ANN structures are:

1. In order to ensure maximum estimating accuracy the ANN structure should include at least 2 PEs for each variable within the model.

2. Contrary to the results found when examining the effect of varying numbers of hidden layers on estimating performance, the above results, (shown in Figure 5.20), indicated that overall the 3-layer network provided the highest estimating accuracy. However, in general to

overcome the tendency of ANN structures to be erratic in terms of their estimating accuracy the ANN structure should include at least 2 hidden layers.

4. **Effect of Number of Variables and Size of Data Sample**. Increasing the number of variables increases the estimating accuracy of the resulting models both in terms of the % Average Absolute Error and the Standard Deviation of % Average Absolute Error. This effect becomes more pronounced as the number of data points used to construct the model decreases. However, both increasing numbers of variables and increasing numbers of data points led to improvements in estimating accuracy. The trends in estimating accuracy shown in Figures 5.22 to 5.43 and Table 5.3 support this observation.

Figure 6.3 has been constructed using values obtained from Table 5.3. This figure and the results contained in Table 5.3 indicate that:

1. The estimating accuracy, of the regression based models, in general increases with increasing numbers of variables but there appears no marked increase when the number of data points used to construct models increases.
2. In contrast the estimating accuracy of the models developed using the 'best' neural network structure are strongly dependent on both the number of data points and number of variables within the model.

3. In all cases the estimating accuracy of the regression models is less than that obtained using models developed using the 'best' ANN structure.

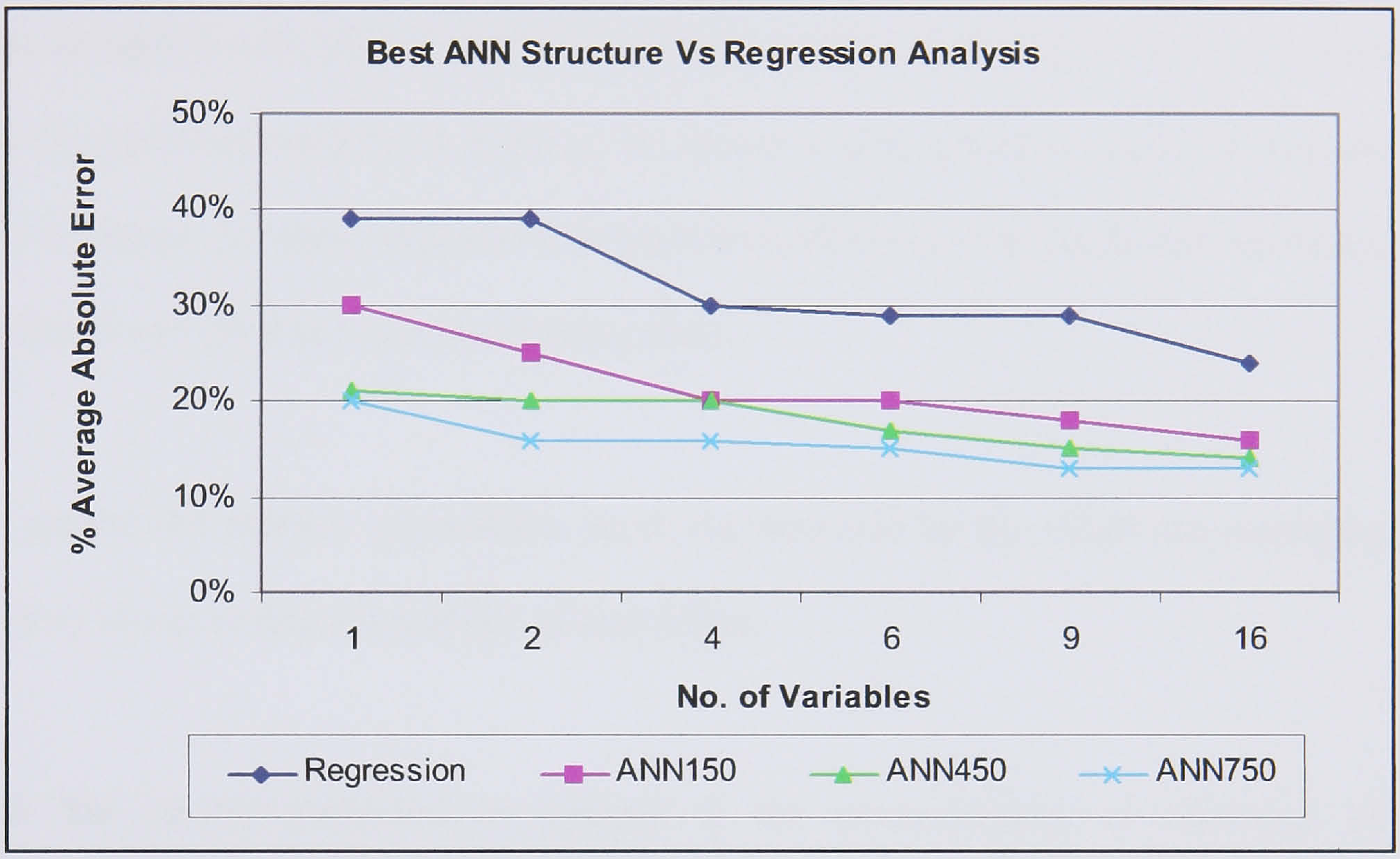

Figure 6.3 Best ANN Structure Vs Regression Analysis

Figure 6.3 indicates that the estimating accuracy of the 1-layer, 2-layer and 3-layer ANN models is closest when the maximum number of variables are employed, i.e. 16. This is to be expected since when using 16 variables all available cost information is being used to train the ANN models. In addition, the rate at which the estimating accuracy increases, as additional variables are included within the model is approximately constant over the entire range, i.e. 1 to 16. This indicates that each variable contributes approximately the same amount to the final cost estimate. This is in agreement with Table 5.44 which illustrates the relative effect of individual variables within the turning model, ie the majority of the variables make similar contributions.

The estimating accuracy obtained when using the 'worst' network structure is poor when compared with that of the 'best' structure and in many cases when compared with the regression models. In addition, the ability of such models to estimate accurate costs is erratic, i.e. there appears to be no relationship between estimating accuracy, number of variables and number of data points.

The greater the number of variables used, the less will be the effect on estimating accuracy of increasing the number of data points.

From the results presented in Chapter 5 the consequences of choosing an inappropriate network structure can be identified, i.e. in all cases the 'best' network structure performed better then the 'worst' network structure in terms of the estimating accuracy of the resulting models. Little evidence is available to suggest that specific ANN structures could be used over a range of applications. Hence, the Taguchi approach adopted in this research represents an efficient method of determining appropriate ANN structures since it allows the number of experiments required for identification to be minimised and, therefore the costs of developing the resulting models.

6.5.1.2 Range of Application Areas

The literature review indicated that ANNs had been used in a variety of application areas and that they were suitable for developing models of both linear and non-linear relationships. The current work has extended the range of costing applications without any problems being encountered. In addition, the applications used contained both linear and non-linear relationships.

Applications within other manufacturing domains have indicated that ANNs are not problem-type or function-type dependent. ANNs are applicable to problems that are difficult to structure for solution purposes, e.g. situations where several items of equipment may share specific cost resources. In addition, the potential exists for linking individual ANNs such that they perform a sequence of tasks, e.g. an initial ANN that groups cost types according to similar criteria and subsequent ANNs developing individual cost models for individual groups.

Hence, it can be concluded with some degree of certainty that there is potentially no limit to the variety of manufacturing processes and tasks for which ANN based cost models can be developed.

In Section 6.5.1.1 it was identified that the relative effect on estimating accuracy of individual PE functions bore little relationship to the overall estimating accuracy of the resulting cost models. The existence of this effect tended to favour the possibility of identifying a generalised or robust ANN structure that was applicable over a wide range of application areas. In order to explore this potential further, experiments were carried out in which models developed using the 'best' artificial neural network structure for one application, (e.g. turning), were used to develop cost models for the other application, (e.g. drilling).

The results of these experiments are presented in Figure 5.46 and displayed in Table 5.4 for ease of analysis. This table indicates the 'robustness' of the best ANN structure that was developed for the turning application, i.e. this was tested using both the turning and drilling data test sets. In both cases the level of estimating accuracy was similar tending to indicate that this model structure could be used within both applications. However, when the 'robustness' of the best drilling ANN structure was tested this resulted in a widely differing estimating accuracy between the two applications, i.e. 26% for turning and 15% for drilling. Although not a conclusive test, the results do tend to indicate that some artificial neural network structures may be more robust then others.

6.5.1.3 Personnel Involved

It has been suggested in the literature that the use of ANNs has important advantages over the use of regression analysis since they are claimed to significantly reduce the level of expertise required by both model developers and users. In certain respects this statement is true, i.e.:

1. Model developers no longer need sufficient depth of process or product knowledge that enables them to understand the form, ie linear or non-linear, of the underlying relationships between costs and the variables that influence these costs. When developing models using regression analysis it is often necessary, in order to maximise model estimating accuracy, to carry out trials using various types and numbers of variables, and make decisions as to whether the resulting regression line will start at the 'origin'. In contrast, ANNs possess strong automatic inference

mechanisms which enable users to generate models with much less manual intervention.

2. The need to identify the relative importance on costs of individual variables is no longer required when using ANN methods. Hence model developers require less process and product expertise.

   When compared with the use of regression analysis, additional areas of knowledge are required for establishing effective artificial neural networks, i.e. these include:

   a. expertise in selecting the data to be used for training the network,
   b. expertise in selecting the order in which data is presented during training,
   c. expertise in selecting data for testing the network, and
   d. expertise in developing the optimum network configuration parameters, i.e. in terms of number of hidden layers, number of processing elements in each layer and choice of transfer functions.

In terms of this last area of expertise, the work undertaken in this research project has made a significant contribution to establishing a formal methodology for identifying suitable network structures and hence removed much of the ANN expertise that would formerly have been required.

A major constraint to the adoption of ANN based cost models within manufacturing industry is the non-iconic nature of the resulting cost model, i.e. to the user the model is merely either a collection of weights, network architecture and nodal transfer functions or in the form of computer code. Unlike using regression analysis, models developed using ANNs will not bear any relationship to the actual variables and variable relationships that exist in practice. Under these circumstances it is difficult to ensure that model users gain confidence in use of such models. In addition, those personnel affected by the outcomes of such models may find it relatively easy to question the validity of such models. In order to maintain confidence in such a model it would be necessary to ensure that its use is frequently audited and at regular intervals the model is updated if possible using actual cost data.

As with regression based methods, expertise is required at the data identification and data collection stages of the model development process to ensure that appropriate variable types are selected for inclusion within the model, and that sufficient cost examples are collected.

6.5.1.4 Data Requirements and Model Development & Operating Costs

The cost of developing and using cost models is closely related to a model's data requirements, i.e. the major time and resource constraint is primarily the data collection stage. The greater the number of variables required within a model, in general, the greater will be the model development costs. In addition, in order to use the model the greater will be the data required to be input into the model in order to obtain the outputted cost.

Within the research literature it appears to be an accepted fact that artificial neural networks require large amounts of input data in order to develop models with high levels of estimating accuracy. To some extent, this has not been found to be the case in the current research where the general result has been the need for less data than that required for the regression technique, i.e. for the same level of estimating accuracy the ANN technique would require much less input data than would the regression technique. An example of this can be found by analysing the results shown in Figures 5.23 to 5.27. These figures show that to achieve a 20% average absolute error level the ANN technique required less than 300 data points to train the network whereas the regression method needed over 750 data points.

Table 5.4 provides the highest levels of accuracy obtained using ANN and regression models. When the best ANN structure, (i.e. developed using turning data, trained with the maximum number of data points and including the maximum number of variables), was used to develop a cost model the resulting accuracy was 18% average absolute error. In terms of the types of cost models used within industry, i.e. high level, low level and rule of thumb (Section 2.3.1), this level of accuracy would, in general, not be acceptable when using a low level model. In addition, although this accuracy would be acceptable when using high level or rule of thumb models, the effort required in terms of data collection may be unacceptable. In order to improve estimating accuracy, complex models such as the turning model would need to be broken up into smaller sub-models, i.e. as illustrated in Section 4.2.1. Each sub-model would contain fewer variable types and hence less potential interactions between functional relationships. Hence, improved accuracy of estimating could result.

Additional costs required when using ANN techniques are the necessity to purchase appropriate ANN software development tools and to train the intended users in the use of these tools. The NeuralWorks Professional II/PLUS software tool used within the current research has been proved reasonably easy to use. This software package was found to reduce the time required to design suitable network architectures. It is particularly suited for performing the experiments identified using Taguchi orthogonal arrays.

6.5.2 Cost Model Development Process

The basic tasks involved in developing cost models have been found to be data identification, data collection and data analysis. The essential aims of these tasks are to identify and collect product, process, cost and time information and to analyse this information in order to quantify the cost estimating relationships that exist.

6.5.2.1 Data Identification & Collection

From Figures 5.44 and 5.45 it can be seen that the artificial neural network approach is capable of identifying the relative effects, on estimating accuracy, of the individual variables within a model. These results show a marked difference between the effects of individual variables within models, i.e. within the turning model there is a 5.5% difference in the relative effect on estimating accuracy between the 16 variables and within the drilling model this effect is 16% between only 4 variables. For example, with respect to the drilling application, the variable "NL" plays a more important role than "TH" in deciding the final process time for a drilling operation. The opportunity exists, therefore, of allowing model developers to establish the relative importance of the costs of individual variables using ANN methods.

Artificial neural networks are trained to minimise the overall error between estimating and actual cost values. In this respect, the data used to train a network, to be representative, must ensure even representation of the variety of cost situations found in practice.

Data collection tasks, when compared with other activities within the cost model development process, can potentially be the most time consuming. The use of ANN methods for developing cost models may provide assistance in reducing these data collection times, i.e.:

- **a.** by reducing the amount of data that is required to be collected, i.e. ANN methods provide improved estimating accuracy, when compared with regression analysis, using less training data,
- **b.** by allowing data items with missing variable values to be used within training sets, i.e. unlike when using regression methods,
- **c.** by removing the need for extensive verification of the collected data, i.e. it is not necessary to find and remove data items with missing variable values, data values that lie outside the range of normal values, data items corrupted by small amounts of 'noise', and
- **d.** by allowing the use of qualitative information.

6.5.2.2 Data Analysis

In terms of improving the data analysis task, i.e. the identification of the cost estimating relationships, within the cost model development process, ANN methods are able to:

a. remove the need to establish the variables that constitute the cost drivers,
b. remove the need to identify the relative importance of each cost driver,
c. remove the need to know the form of the cost function,
d. increase the number of variables that can be considered simultaneously,
e. remove the need for quantitative data by increasing the use of qualitative data,
f. decrease the accuracy of the data items required,
g. reduce the level of data required,
h. increase the accuracy/data detail ratio, i.e. obtained improved accuracy with lower level of data detail,
i. where possible automate data collection tasks, and
j. remove the need to formally structure data.

Chapter 7 Conclusions

It has been identified that global market trends are resulting in the need for manufacturing organisations to offer greater choices of products, greater amounts of product customisation and greater emphasis on minimising total life cycle costs. In order to remain competitive in this changing environment, manufacturing organisations must take more advantage of alternative manufacturing processes and materials, and sustain reduced product development cycles.

In order to support the increased levels of product and process development activity that will be required, and hence remain competitive, it is expected that the quantity, type, accuracy and complexity of cost models will need to be greatly increased. These improvements in quantity and quality of cost models must be possible under conditions where there may be less historical cost data available, less time available to develop cost models and less process expertise available. When considering these changes, this research project has contributed to the support of the cost modelling function in the following ways:

1. The *basic tasks involved in the cost model development process* and the *basic characteristics of cost models* have been identified and their use in providing a framework for the evaluation of alternative modelling techniques demonstrated.

2. Artificial neural networks have been examined as an alternative method of establishing cost models and their main benefits and limitations identified. Here a major limitation has been identified as the lack of existing knowledge or methods

by which to establish suitable ANN structures for specific costing applications. Experimental studies undertaken to compare alternative ANN structures have yielded marked differences in their estimating accuracy, hence demonstrating the importance of ensuring that suitable ANN structures are used.

3. The Taguchi Methodology has been identified and demonstrated for identifying suitable ANN structures and has been shown to provide a method that minimises the experimental effort required.

4. The potential for developing a 'robust' ANN structure, i.e. a structure that can be used over a range of costing applications, has been examined. The results indicate that specific ANN structures could be developed that could be suitable for a range of costing applications.

5. Experiments undertaken to identify the influence of varying the *number of layers* and *number of processing elements per layer* within an ANN structure have shown that in general, increasing the *number of processing elements per layer* and decreasing the *number of layers* leads to an increase in estimating accuracy.

6. Experiments have been undertaken to identify the influence, on the estimating accuracy of the resulting models, of varying the *amount of data used to develop the model* and varying the *number of variables within the model*. As would be expected, increasing the *amount of data used to develop the model* and increasing the *number of variables within the model* in all cases leads to an overall increase in the estimating accuracy of the resulting models. These experiments did,

however, reveal that less variables and lower amounts of cost data are required to achieve a specific level of estimating accuracy than when using regression analysis. Hence, data identification and collection tasks would be simplified.

7. Improvements, over the use of regression based models, in the estimating accuracy of cost models can be obtained. However, the levels of accuracy obtained during the experimentation would not be acceptable in situations where highly repetitive job tasks were being costed.

8. The expertise required from the personnel who develop and use ANN cost models would differ from that required when using regression analysis. In general less process and product expertise would be required but more expertise would be required to establish suitable ANN structures and suitable methods of training networks. However, the need for this latter expertise could be removed when more knowledge of the use of ANNs becomes available.

Chapter 8 Further Work

From the research undertaken further work areas have been identified:

1. An investigation needs to be undertaken aimed at identifying the relationships between the individual function types within processing elements and the types of functional relationships, (e.g. linear and non-linear), that make up the actual cost models. The aim of this work would be to determine if relationships existed and whether these relationships could be used to design the processing structures of ANNs for particular costing applications, such that optimum levels of estimating accuracy could be achieved.

2. The work undertaken within this research project has made a significant contribution to establishing a formal methodology for identifying suitable network structures and hence removed much of the ANN expertise that would formally have been required. However, further work is needed to resolve the issues of how many *hidden layers* and how many *processing elements per layer* should be used to construct the ANNs. As with the further work described above, these factors must be investigated with respect to their relationship with the factors that describe the resulting cost models, e.g. numbers of variables within the model, functional relationships of these variable.

3. The research undertaken indicated that there was no relationship between the individual effects, on estimating accuracy, of specific function types within a

processing element and the overall accuracy of the resulting ANN cost model. This could have important implications when attempting to identify 'robust' ANN structures, hence further work needs to be conducted to establish the true cause of this effect and its relationship to the robustness of individual artificial neural network structures.

4. Data identification and collection are time consuming tasks within the overall cost modelling process. The use of artificial neural networks has indicated that improvements could be made in these areas. This needs to be explored further with the objective of developing a lean methodology for both tasks, i.e. a methodology that minimizes the number of variables and amount of data that needs to be collected.

5. In order to reduce the levels of expertise required to make use of ANN technology, further research also needs to be carried out to define the precise rules for:

i) selecting the data to be used for training a network,

ii) selecting the order in which data is presented during training, and

iii) selecting data for testing the network.

References

American Supplier Institute Inc, 1989, Taguchi Methods: Implementation Manual, ASI, Dearborn, MI.

Apgar, H. E. and Daschbach, J. M., 1987, Analysis of Design through parametric cost estimation techniques, in Eder, W. E (Ed.) *Proceedings of international conference on Engineering Design*, Vol 2.

Arizono, I., Yamamoto, A. and Ohta, H., 1992, Scheduling for minimising total actual flow time by artificial neural networks, *International Journal of Production Research*, Vol. .30, No. 3, pp.503-511, ISSN: 0020-7543.

Bavishi, J., 1997, Estimating software as a DFM tool, *Manufacturing Engineering*, Vol. 118, No. 3, pp. 92-98, ISSN: 0361-0853.

Becker, J. and Prischmann, M., 1993, Supporting the design process with neural networks - a complex application of co-operating neural networks and its implementation, *Journal of Information Science and Technology,* Vol. 3, pp. 79-95.

Bendell, A., 1988, Introduction to Taguchi Methology, Taguchi Methods: Proceeding of the 1988 European Conference, Elsevier Applied Science, London, England, pp. 1-14.

Bidanda, B., Kadidal, M. and Billo, R. E., 1998, Development of an intelligent castability and cost estimation system, *International Journal of Production Research*, Vol. 36 No.2, pp. 547-568, ISSN: 0020-7543.

Bloch, C. and Ranganathan, R., 1991, Process based cost modelling, *IEEE/CHMT International Electronic Manufacturing Technology Symposium*, pp. 406-412, 0000-0406.

Bode, J., 1998, Neural Networks for Cost Estimation, *Cost Engineering*, Vol. 40, No.1, pp. 25-31, ISSN: 0274-9696.

Bode, J., 2000, artificial neural networks for cost estimation: simulations and pilot application, *International Journal of Production Research,* Vol. 38, Part. 6, pp. 1231-1254, ISSN: 0020-7543.

Bode, J., Hu, Y., Liu, P. and Shu, B., 1995a, Cost estimation in new product development: knowledge pluralism, knowledge granularity, and agent based representation in Q. Sun, Z. Tang and Y.Zhang (eds) Computer Applications in Production and engineering, London : Chapman & Hall, pp. 1749-1754.

Bode, J., Ren, S.J. & Shi, Z.Z., 1995b, Application of 3-layer Perceptrons to cost estimation, *Proceedings of the 1995 IEEE International Conference on Neural Networks*, Vol. 4, Part 4 (of) 6, pp. 1749-1754, ISBN: 0-7803-768-3.

Bode, J., Ren, S., Luo, S., Shi, Z., Zhou, Z., Hu, H., Jiang, T. and Liu, B., 1995c, Neural networks in new product development, representation in Q. Sun, Z. Tang and

Y. Zhang (eds) Computer Applications in Production and engineering, London : Chapman & Hall, pp. 659-666, ISBN: 0412707705.

Bode, J. and Ren, S., 1996, Neural networks for cost estimation – benchmarks and pilot study, Research Report, Tsinghua University, CIMS-ERC, Beijing/China.

Boothroyd, G. and Reynolds, C., 1989, Approximate cost estimates for typical turned parts, *Journal of Manufacturing Systems,* Vol. 8, Part 3, pp. 185-193, ISSN: 0278-6125.

Bryne, D. M. and Taguchi, G., 1986, The Taguchi Approach to Parameter Design, ASQC Quality Congress Transactions, Anaheim, CA, pp.168, 1986.

Burnett, R. C., 1996 A Trade-Off Model Between Cost and Reliability During the Design Phase of Software Development, PhD Thesis, Newcastle Upon Tyne.

Busch, J., 1994, Cost modelling as a technical management tool, *Journal of the Research Technology Management*, Vol. 37, No. 2, Nov-Dec, pp. 50-56, ISSN: 0895-6308.

Carpenter, G. A. and Grossberg, S., 1983, A massively parallel architecture for a self-organising neural pattern recognition machine, *Computer Vision, Graphics, and Image Processing*, Vol. 37, pp. 54-115, ISSN: 0734-189X.

Carpenter, G. A. and Grossberg, S., 1987, ART 2: Self-organisation of stable category recognition codes for analog output patterns, *Applied Optics,* Vol. 26, pp. 4919-4930, ISSN: 0003-6935.

Carpenter, G. A. and Grossberg, S., 1988, The ART of adaptive pattern recognition by a self-organising neural network, *Computer,* Mar, pp. 77-88, ISSN: 0018-9162.

Carpenter, G. A. and Grossberg, S., 1990, ART 3 hierarchical search: Chemical transmitters in self-organising pattern recognition architectures, *Proc. Int. Joint Conf. on Neural Networks*, Vol. 2, pp. 30-33.

Cawthorne-Nugent, M., Daluz, V. J. and Watson, P. A., 1989, An intelligent knowledge based system for cost estimating in the make-to order environment, *Journal of Computer-Aided Engineering,* Vol. 6, No. 4, pp. 121-127, ISSN: 0263-9327.

Cebesoy, T., 1993, Cost Modelling System for Discontinuous Surface Mining Equipment, PhD Thesis, Nottingham University.

Chang T-C., 1990, Expert process planning for manufacturing, Addison Wesley, Reading, ASIN: 0201182971.

Chin, K-S. and Wong, T. N., 1996, Developing a knowledge-based injection mould cost estimation system by decision tables, *International Journal of Advanced Manufacturing Technology*, Vol. 11, pp. 353-364, ISSN: 0268-3768.

Croker, D. C., 1967, Intercorrelation and the Utility of Multiple Regression in Industrial Engineering, *The Journal of Industrial Engineering,* Vol. 18, No.1, pp. 79-85, ISSN: 1072-4761.

Cullen, J. and Hollingum, J., 1987, Implementing Total Quality, Springer-Verlag, New York, N. Y, 1987, ISBN: 0023442247.

Cunningham, J. J. and Dixon J. R., 1988, Designing with Features: The Origin of Features', *Computers in Engineering*, ASME, pp. 237-243.

Currie, R. M., 1973, Work Study, Unwin Brothers Limited, ASIN: 0273009591.

Dale, B. and Plunkett, J., 1991, Quality Costing, Chapman and Hall, London, England, ISBN: 0566082608.

Dean, E. B., 1989, Cost analysis: research directions, *Second Joint National Conference of the National Estimating Society and the Institute of Cost Analysis,* Washington DC, 5-7 July.

Dean, E. B. ,1990, The Design-To-Cost-Manifold, presented at *the International Academy of Astronautics Symposium on Space Systems Cost Methodologies and Applications*, San Diego, CA, USA, 10-11 May, IAA-CESO-11.

De la Garza, J. M. and Rouhana, K. G., 1995, Neural networks versus parameter-based applications in cost engineering, *Journal of Cost Engineering*, Vol. 37, No. 2, Feb, pp. 14-18, ISSN: 0274-9696.

De Rosa, Catherine., 1999, Customer Trade: the Next Industrial Revolution, Symix Systems Inc.

Dertouzos, M. L., Lester, R. S. and Solow, R. M., 1989, Made in America: Reading the Productive Edge, Harper Perennial, New York, NY.

De Vasconcellos, N. and Yoshimura, M., 1999, Life cycle cost model for acquisition of automated systems, *International Journal of Production Research*, Vol. 37, No. 9, pp. 2059-2076, ISSN: 0020-7543.

Dewhurst, P. and Boothroyd, G., 1988, Early cost estimating in product design, *Journal of Manufacturing Systems*, Vol. 7, Part 3, pp. 183-191, ISSN: 0278-6125.

Dhavale, D.G., 1990, A manufacturing cost model for computer-integrated Manufacturing systems, *International Journal of Operations and Production Management*, Vol. 10, part 8, pp. 5-18, ISSN: 0144-3577.

Dick, J. H., 1993, Cost Modelling and Concurrent Engineering for Testable Design, PhD Thesis, Brunel University.

Edwards, W. C. and Wong, J. F., 1987, A computer model to estimate capital and operating costs, *Cost Engineering* Vol. 29, No. 10, pp. 15-23, ISSN:0274-9696.

Ehrlenspiel, K. and Schaal, S., 1992, In CAD integrierte Kostenkalkulation, Konstruktion, Vol. 44, pp. 407-414.

Elsen, S. H. and Followell, R. F., 1993, The total costs of quality: what else should be contemplated?, *Quality and Reliability Engineering International*, Vol. 9, pp. 203-209.

Eversheim, W., Neuhausen, J. and Sesterhenn, M., 1998, Design-to-Cost for production systems, *CIRP Annals-Manufacturing Technology*, Vol. 47, No. 1, pp357-360, ISSN: 0007-8506.

Feng, C.-X., Kusiak, A. and Huang, C.-C., 1996,Cost evaluation in design with form features, *Journal of Computer-Aided Design,* Vol. 28, No.11, pp. 879-885, ISSN: 0010-4485.

Fisher, R. A., 1925, Statistical Methods for Research Workers, Oliver & Boyd, London, ASIN: 0028-447301.

Fowlkes, W. Y. and Creveling, C. M., 1995, Engineering Methods for Robust Product Design: Using Taguchi Methods in Technology and Product Development, Addison-Wesley Publishing Company, Reading, MA, USA, ISBN: 0-201-63367-1.

Fukushima, K., 1975, Cognitron: A self-organising multilayered neural network. *Biological Cybernetics*, Vol. 20, pp. 121-136, ISSN: 0340-1200.

Fukushima, K. and Miyaka, S., 1980, Neocognitron : A self-organising neuralnetwork model for a mechanism of pattern recognition unaffected by shift in position, *Biological cybernetics*, Vol. 36, pp.193-202, ISSN: 0340-1200.

Gantois, K. and Morris, A. J., 1999, Incorporation of manufacturing information into an MDO environment, *The Aeronautical Journal*, Vol. 103, Part 1026, August, pp. 383-388, ISSN: 0001-9240.

Geman, S., Bienenstock, E. and Doursat, R., 1992, Neural network and the bias/variance dilemma, *Neural Computation*, Vol. 4, pp. 1-58, ISSN: 0941-0643.

Gingrich, C. G., Kuespert, D. R. and McAvoy, T. J., 1992, Modelling human operators using neural networks, *ISA Transactions*, Vol. 31, No. 3, pp. 81-90, ISSN: 0019-0578.

Gövekar, E., Grabec, I. and Peklenik, J., 1989, Monitoring of a frilling process by a neural network, *The 21st CIRP International Seminar on Manufacturing Systems*, Stockholm, Sweden.

Gunter, B., 1987, A perspective on the Taguchi methods, *Quality Progress*, June, pp. 44-52, ISSN: 0033-524X.

Gutman, N, 1981., How to keep product costs in line, *Machine Design*, pp. 50-53.

Hallberg, B., Kinkoph, S. and Ray, B., 1997, Special Edition Using Microsoft Excel97, Que Corporation, ISBN: 0-7897-1399-3.

Haykin, S., 1992, Blind equalisation formulated as a self-organised learning process, *Proceedings of the Twenty-sixth Asilomar Conference on Signals, Systems and Computers,* Vol. 1, pp. 346-350.

Hebb, D. O., 1949, The Organization of Behavior: A Neuropsychological Theory, New York: John Wiley, ISBN: 0471367273.

Hegde, G. G., 1994, Life cycle cost : a model and applications, IIE Trans, Vol. 26, No. 6, pp. 56-62, ISSN: 0740-817X.

Hill, T. M., Forster, R.J., and Smith, G., 1994, A feature based approach to detail and assembly costing in the aerospace industry, *Proceedings of the Tenth National Conference on Manufacturing Research,* pp. 249-253, ISBN: 0-7484-0254-3.

Hinton, G. E., Sejnowski, T. J. and Ackley, D. H., 1984, Boltzmann machines: Constraint satisfaction networks that learn, Tech. Rep. CMU-CS-84-119, Dept. Comp. Sci., Carnegie-Mellon University.

Hinton, G. E. and Sejnowski, T. J., 1986, Learning and relearning in Boltzmann machines, Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Vol. 1: Foundations, Cambridge, MA: MIT Press, pp. 282-317.

Hopfield, J. J., 1982, Neural networks and physical systems with emergent collective computational abilities," Proc. Natl. Acad. Sci., Vol.79, pp. 2554-2558, ISSN: 0027-8424.

Hopfield, J. J., 1984, Neurons with graded response have collective computational properties like those of two state neurons, *Proc. Natl. Acad. Sci.,* Vol. 81, pp. 3088-3092, ISSN: 0027-8424.

Hundal, M.S.,1993, Rules and models for low-cost design, *Proceeding of ASME Design for Manufacturability Conference*, pp. 75-84.

Hwang, G. H. and Aspinwall, E. M., 1996, Quality cost models and their application: a review, *Total Quality Management,* Vol. 7, No. 3, pp. 267-281, ISSN: 0954-4127.

Ito, Y., Ogawa, H. and Tani, H., 1996, A new cost model, CPO, for the evaluation of FAB performance, *IEICE Trans. Electron*, Vol. E79-C, No. 3, March, pp. 301-305.

Kacker, R. N., 1986, Taguchi's quality philosophy: Analysis and commentary. Quality Progress, December, pp. 21-29, ISSN: 0033-524X.

Kamal, S. and Burke, L.I., 1996, FACT: a new neural network-based clustering algorithm for group technology, *International Journal of Production Research*, Vol. 34, No. 4, pp. 919-946, ISSN: 0020-7543.

Kamarthi, S.V., Kunara, S.T., Yu, F.T.S and Ham. I., 1990, Neural networks and their applications in component design data retrieval, *Journal of Intelligent Manufacturing*, Vol. 1, No.2, pp. 125-140, ISSN: 0953-9875.

Kaparthi, S. and Suresh, N. C., 1991, A neural network system for shape-based classification and coding of rotational parts, *International Journal of Production Research*, Vol. 29, No. 9, pp. 1771-1784, ISSN: 0020-7543.

Kingsman, B. G. and de Souza, A. A., 1997, A knowledge-based decision support system for cost estimation and pricing decisions in versatile manufacturing companies, *International Journal of Production Economics*, Vol. 53, No. 2, Nov 20, pp. 119-139, ISSN: 0925-5273.

Knapp, G. M. and Wang, H. –P., 1992, Acquiring storing and utilising process planning knowledge using neural networks, *Journal of Intelligent Manufacturing*, Vol. 3, No. 5, pp. 333-344, ISSN: 0953-9875.

Kohonen, T., 1977, Associative Memory: A System-Theoretical Approach, Berlin: Springer-Verlag, ISBN: 0387080171.

Kohonen, T., 1984, Self-Organization and Associative Memory, Berlin: Springer-Verlag, ISBN: 0387513876.

Kohonen, T., 1987 Adaptive,associate, and self-organization functions in neural computing, *Applied Optics,* Vol. 26, pp. 4910-4918, ISSN: 0003-6935.

König, T., 1995, Konstruktionsbegleitende Kalkulation auf der Basis von Ähnlichkeitsvergleichen (Bergisch Gladbach: Eul), Germany.

Kremen, G. Z., Elsayed, E.A. and Ribeiro, J.L., 1994, Machining time estimation for magnetic abrasive processes, *International Journal of Production Research*, Vol. 32, Part. 12, pp. 2817-2825, ISSN: 0020-7543.

Lederer, A.L. and Prasad, J., 1993, Systems development and cost estimating challenges and guidelines, *Journal of Information Systems Management*, Fall , pp. 37-41.

Lee, A., Cheng, H. and Balakrishnan, J., 1998, Software development cost estimation: integrating neural network with cluster analysis, *Journal of Information and Management*, Vol. 34, No. 1, Aug 5, pp. 1-9, ISSN: 0378-7206.

Lee, R. J. V. and Young, R. I. M., Design for manufacture: an approach to software support in a concurrent engineering environment, 1994, *IEE Factory 2000 – Advanced Factory Automation, Conference Publication No. 398,* 3 –5 October, pp. 593-600.

Leibl, P., Hundal, M. and Hoehne, G., 1999, Cost calculation with a feature-based CAD system using modules for calculation, comparison and forecast, *Journal of Engineering Design*, Vol. 10, No. 1, pp. 93-102, ISSN: 0954-4828.

Li, Y., Mills, B., Moruzzi, J. L. and Rowe, W. B., 1994, Grinding wheel selection using a neural network, *Proceedings of the Tenth National Conference on Manufacturing Research*, pp. 597-601, ISBN: 0-7484-0254-3.

Lippmann, R. P., 1987, An introduction to computing with neural nets, IEEE-ASSP-Magazine, Vol. 4, No.2, April, pp. 4-22.

Logothetis, N. and Salmon, J. P., 1988, Tolerance design and analysis of audio-circuits, Taguchi Methods: *Proceedings of the 1988 European Conference*, pp. 161-175.

Looi, C. K., 1992, Neural network methods in combinatorial optimisation, *Journal of Computers Operations Research*, Vol. 19, No. 3-4, pp. 191-208, ISSN: 0305-0548.

Luong, L. H. S. & Spedding, T., 1995, An integrated system for process planning and cost estimation in hole making, *International Journal of Advanced Manufacturing Technology*, Vol. 10, Part 6, pp. 411-415, ISSN: 0268-3768.

Martinez, E. E., Smith, A.E. and Idanda, B., 1994, Reducing waste in casting with a predictive neural model, *Journal of Intelligent Manufacturing*, Vol. 5, No. 4, pp. 277-286, ISSN: 0953-9875.

McCulloch, W. S., and Pitts, W. A., 1943, Alogical calculus of the ideas imminent in nervous activity, *Bulletin of Mathematics and Biophysics*, Vol. 5, pp. 115-133, ISSN: 0007-4985.

Meisl, C. J., 1990, Parametric cost analysis in the TQM environment, *12th Annual Conference of International Society of Parameteric Analysts*, San Diego, CA.

Michaels, J. V. and Wood, W.P., 1989, Design to Cost, Wiley and Sons, New York.

Mileham, A.R., Currie, G.C., Miles, A.W. & Bradford, D. T., 1993, A parametric approach to cost estimating at the conceptual stage of design, *Journal of Engineering Design*, Vol. 4, No.2, pp. 117-125.

Miles, J. R., 1988, Cost Modelling for VLSI Circuit Conversion to Aid Testability, PhD Thesis, Brunel University.

Minsky, M., 1954, Neural Nets and the Brain, PhD Dissertation, Princeton University.

Monks, J. G., 1995, Operation Management, 2nd ed, McGRAW- HILL, ISBN: 0-07-042764-X.

Mulkezi, L., 1994, The Design of Project Estimating Systems, PhD Thesis, University of Birmingham.

Mundel, M. E., 1978, Motion and Time Study : Improving Productivity, 5th ed, Englewood Cliffs; London : Prentice-Hall, ISBN: 0-13-602987-6.

The NeuralWare Inc., 1996, Advanced Reference Guide for Professional II/PLUS.

Ostwald, P. Cost Estimating, 4nd Edition, 1988, Prentice-Hall, Englewood Cliffs, New Jersey, pp. 41.

Ou-Yang, C. & Lin, T.S., 1997, Developing an integrated framework for feature-based early manufacturing cost estimation, *International Journal of Advanced Manufacturing Technology*, Vol. 13, Part 9, pp. 618-629.

Ott, R. L., 1992, An introduction to Statistical Methods and Data Analysis, 4th Edition, Duxbury Press, pp. 470-474, ISBN: 0-534-93150-2.

Park, W. R., 1973, Cost Engineering Analysis, John Wiley & Sons, New York, ISBN: 0-471-65914-2.

Peace, G. S., 1993, Taguchi Methods: A Hands-On Approach, Addison-Wesley Publishing Company, Reading, MA, USA.

Phadke, S. M., 1989, Quality Engineering Using Robust Design, Prentice Hall, Englewood Cliffs, N. J, ISBN: 0-201-56311-8.

Porter, L. J. and Rayner, P., 1992, Quality costing for total quality management, *International Journal of Production Economics*, Vol. 27, No. 1, pp. 69-81, ISSN: 0925-5273.

Rao, G.N., Grobler, F. and Kim, S., 1993, Conceptual cost estimating: A hybrid neural-expert system approach, *Proceeding of the 5 Th International Conference on Computing in Civil and Building Engineering*, 7 – 9 June, pp. 423-430.

Rehman, S., Guenov, M., 1998, A methodology for modelling manufacturing costs at conceptual design, *Journal of Computers and Industrial Engineering*, Vol. 35, No. 3-4, pp. 623-626, ISSN: 0360-8352.

Rosenblatt, 1958, The perceptron: A probabilistic model for information storage and organisation in the brain, *Psychoanalytic Review*, Vol. 65, pp. 386-408.

Ross, P. J., 1988, Taguchi Techniques for Quality Engineering: Loss Function, Orthogonal Experiments, Parameter and Tolerance Design, McGraw-Hill Book Company, New York, NY, USA.

Sanchez, M., Kundu, A.K., Hinds, B. K. and Raghunathan, S., 1998, Amethodology for assessing manufacturing cost due to tolerance of aerodynamic surface features on turbofan nacelles, *International Journal of Advanced Manufacturing Technology*, Vol. 14, pp. 894-900.

Sette, S., Boullart, L. and Van Langenhove, L., 1996, Optimising a production process by a neural network/genetic algorithm approach, *Journal of Engineering Applications of Artificial Intelligence*, Vol. 9, No.6, pp. 681-689, ISSN: 0952-1976.

Sha'at, K. K., 1993, A Stochastic Cost Engineering System for Construction Projects Through the Rational Bill of Quantities, PhD Thesis, University of Leeds.

Shtub, A. and Versano, R., 1999, Estimating the cost of steel pipe bending, a comparison between neural networks and regression analysis, *International Journal of Production Economics,* Vol. 62, Part3, pp. 201-207, ISSN: 0925-5273.

Shtub, A. and Zimerman, Y., 1993, Neural-network-based approach for estimating the cost of assembly systems, *International Journnal of Production Economics*, Vol. 32, No. 2, Sep. pp. 189-207, ISSN: 0925-5273.

Smith, A.E. and Mason, A.K., 1997, Cost estimation predictive modelling: Regression versus neural network, *Journal of the Engineering Economist*, Vol. 42, No. 2, Winter pp. 137-161.

Song, A. A., Mathur, A. and Pattipati, K. R., 1995, Design of process parameters using robust design techniques and multiple criteria optimisation, IEEE Transactions on Systems, Man, and Cybernetics, San Antonio, TX, USA, 2-5 October, pp. 2572-2577, ISSN: 0018-9472.

Stalk, G. H., Hout, T. M., 1990, Competing against time: How time based competition s reshaping global markets. *Free Press*, New York.

Stevenson, W. J., Production / Operations Management, 1993, 4th ed, Homewood, IL: Irwin, ISBN: 0-256-10828-5.

Stockton, D. J., 1983, Improving the new product development process, PhD Thesis, Loughborough University.

Stockton, D. J., 2000, Improving the Cost Model Development Process: EPSRC Deliverables Report No.2, Ref. No. GR/M 58818, De Montfort University.

Stockton, D. J., Forster, R and Messner, B., 1998, Developing Time Estimating Models for Advanced Composite Manufacturing Processes, Aircraft Engineering and Aerospace Technology, Nov/Dec, ISSN: 0002-2667.

Stockton, D. J. and Wang, Q., 1999, Applying advanced modelling techniques to cost estimating, *Conference of Association of Cost Engineers: Engineering Manufacturing Committee*, March, De Monfort University.

Sullivan, L. P., 1987, The power of Taguchi methods, *Quality Progress*, June, pp. 76-79, ISSN: 0033-524X.

Taguchi, G., 1986, Introduction to Quality Engineering: Design Quality into Products and Processes, Asian Productivity Organisation, Distributed by American Supplier Institute Inc., Dearborn, MI.

Taguchi, G., 1987, System of Experimental Design: Engineering Methods to optimise Quality and Minimise Costs, Vols. 1& 2, UNIPUB/Kraus International Publications, White Plains, NY, USA.

Taguchi, G. and Yokoyama, Y., 1994, Taguchi Methods: Design of Experiments, American Supplier Institute, Dearborn MI, in Conjunction with the Japanese Standards Association, Tokyo, Japan.

Teng, S.-H. G. and Garimella, S. S., 1998, Manufacturing cost modelling in printed wiring board assembly, *Journal of Manufacturing Systems*, Vol. 17, No. 2, pp. 87-96, ISSN: 0278-6125.

Thorstensen, T. A. and Rasmussen, M., 1999, A cost model for condition based overhaul/replacement, *Journal of Quality in Maintenance Engineering,* Vol. 5, No. 2, pp. 102-113.

Tippett, L. C. H., 1934, Application of statistical methods to the control of quality in industrial production, *Manchester Statistical Society*, England.

Turney, P. B. B., 1991, How activity-based costing helps reduce cost, *Journal of Cost Management*, Vol. 4, No. 4, pp. 29-35.

Udo, G. J., 1992, *Neural networks applications in manufacturing process, Proceeding of the 14th Annual International Conference on Computers and Industrial Engineering,* Vol. 23, No. 1-4, pp. 97-100, ISSN: 0360-8352.

Venkatachalam, A. R., 1990, A knowledge-based approach to design for manufacturability, PhD Dissertation, The University of Alabama.

Venugopal, V. and Narendran, T. T, 1992, Neural network model for design retrieval in manufacturing systems, *Computers in Industry*, Vol. 20, pp. 11-23, ISSN: 0166-3615.

Wang, Q. and Stockton, D. J., 1999, Process time estimating using neural networks, *Proceeding of 15th International Conference in Computer-Aided Production Engineering*, Durham University, April, pp. 201-206, ISBN: 0-9535558-0-1.

Wang, Q. and Stockton, D. J., 2000, Process cost modelling using neural networks, *International Journal of Production Research*, Vol. 38, No. 16, pp. 3811-3821, ISBN: 0020-7543.

Weyuker, E. J., 1999, Evaluation techniques for improving the quality of very large software systems in a cost-effective way, *The Journal of Systems and Software*, Vol. 47, pp. 97-103, ISSN: 0164-1212.

Wild, R., 1985, Essentials of Production and Operations Management, London: Holt, Rinehart and Winston Ltd, 2nd ed, ISBN: 0039105857.

Wille, R., 1990, Landing gear weight optimisation using Taguchi analysis, *49th Annual International Conference of Society of Allied Weight Engineers Inc*, Chandler, AR.

Winchell, W., 1989, Realistic Cost Estimating for Manufacturing: Second Edition, Society of Manufacturing Engineers, ISBN: 0-87263-364-0.

Wooding, P., 1997, We know what we have to do, We know where we have to do it. General Motors' Chairman Jack Smith spells out the way forward to its suppliers of the year, Automotive Souring, 5/4, pp. 36-52.

Yeo, S. H., Ngoi, B. K. A. and Chen, H., 1998, Process sequence optimisation based on a new cost-tolerance model, *Journal of Intelligent Manufacturing*, Vol. 9, No. 1, pp. 29-37, ISSN: 0956-5515.

Yoshikawa, T., Innes, J. and Mitchell. F., 1990, Cost tables : A foundation of Japanese cost management, *Journal of Cost Management*, Fall, pp. 30-36.

Zhang, Y. F., Fuh, J. Y. H. and Chan, W. T., 1996, Feature-based cost estimation for packaging products using neural networks, *Journal of Computers in Industry*, Vol. 32, No.1 pp. 95-113, ISSN: 0166-3615.

Bibliography

1. Aderoba, A., 1997, A generalised cost-estimation model for job shops, *International Journal of Production Economics*, Vol. 53, Part 3, pp. 257-263, ISSN: 0925-5273.

2. Adzima, J. C., Elazar, S., Ketchie, W. D., Riordan, W. J. and Anjard, R. P., 1991, Advantages of process modelling as a key manufacturing tool to improve process efficiency and reduce costs, *IEEE/CHMT International Electronic Manufacturing Technology Symposium*, pp. 98-101.

3. Altmann, C., Kittel, I., and Kimura, F., 1994, Estimation of production costs using virtual monitoring: a conceptual framework, *Journal of Design and Manufacturing*, Vol. 4, pp. 187-194, ISSN: 0962-4694.

4. Amsler, B. M., Busby, J. S. and Williams, G. M., 1993, Combining activity-based costing and process mapping: a practical study, *Journal of Integrated Manufacturing Systems*, Vol. 4, No. 4, pp. 10-17.

5. Antony, J. J., 1998, Problem classification in practice, *Manufacturing Engineer*, April, pp. 75-78, ISSN: 0956-9944.

6. Antony, J. J., 1999, Systematic trial and error, *Manufacturing Engineer*, February, pp. 28-29, ISSN: 0956-9944.

7. Antony, J. J., Hughes, M. & Kaye, M., 1999, Reducing manufacturing process variability using experimental design technique: a case study, *Journal of Integrated Manufacturing Systems*, Vol. 10, No. 3, pp. 162-169.

8. Barschdorff, D., and Monostori, L., 1991, Neural networks - their applications and perspectives in intelligent machining, *Computers in Industry*, Vol. 17, pp. 101-119, ISSN: 0166-3615.

9. Becker, J. and Prischmann, M., Supporting the design process with neural networks - a complex application of co-operating neural networks and its implementation, *Journal of Information Science and Technology*, Vol. 3, pp. 79-95.

10. Bidanda, B., Kadidal, M. and Billo, R. E., 1998, Develpoment of an intelligent castability and cost estimation system, *International Journal of Production Research*, Vol. 36 No. 2, pp. 547-568, ISSN: 0020-7543.

11. Brewer, R. F., 1998, What is wrong and what is right with Taguchi designs, *Industrial Engineering Solutions'98 Conference Proceedings*, Canada, pp. 100-103.

12. Canz, T., and Jagdale, S., 1995, Decision support for manufacturing using artificial neural-networks, *Journal of Materials processing Technology*, Vol. 52, Part. 1, pp. 9-26, ISSN: 0024-0136.

3. Carr, R. I., 1989 Cost-estimating principles, *Journal of Construction Engineering & Management*, Vol. 115, Part. 4, pp. 545-551, ISSN: 0733-9364.

4. Cass, R., and Radl, B., 1995, Adaptive process optimisation using functional-link networks and evolutionary optimisation, IFAC Artificial Intelligence in Real-Time Control, pp. 253-258.

5. Choi, C. K. & Ip, W. H., 1999, A comparison of MTM and RTM, *Work Study*, Vol. 48, No. 2, pp. 57-61.

6. Colmer, G., Dunkley, M., Gray, K., Pugh, P. and Williamson, A., 1999, Estimating the cost of new technology products, *International Journal of Technology Management*, Vol. 17, No. 7-8, pp. 840-846.

7. Donald, D. M., 1971, Instant time standards, *Journal of Industrial Engineering*, Vol. 3, No.11, pp. 24-27, ISSN: 0022-183X.

8. Fan, H.-T. and Wu, S.M., 1995, Case studies on modelling manufacturing processes using artificial neural networks, *Transactions of the ASME Journal of Engineering for Industry*, Vol. 117, No. 3, pp. 412-417, ISSN: 0022-0817.

9. Funahashi, K., 1989, On the approximate realisation of continuous mappings by neural networks, *Neural Networks* , Vol. 2, pp. 183-192, ISSN: 0893-6080.

20. Goodman, P. A., 1992, Application of cost-estimation techniques: industrial perspective, *Journal of Information and Software Technology*, Vol. 34, No. 6, pp. 379-382.

21. Huang, S. H. and Zhang, H.-C., 1994, Artificial neural networks in manufacturing: concepts, applications, and perspectives, *IEEE Trans Components, Packaging & Manufacturing Technology – A*, Vol. 17, Part 2, pp. 212-228, ISSN: 1083-4400.

22. Humphreys, K. K. and Katell, S., 1981, Basic Cost Engineering, Dekker, New York, pp. 218.

23. James, A. B., 1998, Feature costing: beyond ABC, *Journal of Cost Management*, Vol. 12, No.1, pp. 6-12.

24. Jeng, W. H. and Liang, G. R., 1998, Automated manufacturing system design methodology based on a tripe flow model, *International Journal of Industrial Engineering*, Vol. 5, No. 1, March , pp. 17-27.

25. Keeler, J., 1992, Version of neural networks and fuzzy logic for prediction and optimization of manufacturing process, *SPIE Application of Artificial Neural Networks III, Vol.* 1709, pp. 447-456.

26. Kingsman, B. G. and de Souza, A. A., 1997, A knowledge-based decision support system for cost estimation and pricing decisions in versatile manufacturing

companies, *International Journal of Production Economics*, Vol. 53, No. 2, Nov 20, pp. 119-139, ISSN: 0925-5273.

27. Lippmann, R. P., 1995, An introduction to computing with neural nets, *IEEE Acoustics, Speech, and Signal Processing Magazine*, Vol. 4, pp. 4-22, ISSN: 0740-7467.

28. Looi, C. K., , 1992, Neural network methods in combinatorial optimization, *Journal of Computers Operations Research*, Vol. 19, No. 3-4, pp. 191-208, ISSN: 0305-0548.

29. Ludema, K. C., Caddell, R. M. and Atkins, A. G., , 1987, Manufacturing Engineering Economics and Processes, Prentice-Hall, Inc pp. 20-32, ISBN: 013555825.

30. Mager, R.P., 1993, Valuing production using engineered costs, *Journal of Cost Accounting*, Vol. 74, No. 9, pp. 50-53.

31. Marx, W. J., Mavris, D. N. and Schrage, D. P., 1998, Cost/time analysis for theoretical aircraft production, *Journal of Aircraft*, Vol. 35, No. 4, July -August pp. 637-646, ISSN: 0021-8669.

32. Nilsson, N. J., 1965. Learning Machines: Foundations of Trainable Pattern Classifiers, New York: McGraw-Hill.

3. Putnam, L. H. & Myers, W., 1997, How solved is the cost estimation problem. *IEEE Software,* Vol. 14, No. 6, pp. 105-107, ISSN: 0740-7459.

4. Rovatti, R. & Guerrieri, R., 1996, Fuzzy sets of rules for system identification. *IEEE Transactions on Fuzzy Systems*, Vol. 4, No. 2, pp. 89-101, ISSN: 1063-6706.

5. Schey, J.A., 1977, Introduction to Manufacturing processes, McGraw-Hill , pp. 350-367, ISBN: 0070552746.

6. Stewart, R. D., and Wyskida, R. M., 1987, Cost Estimator's Reference Manual, New York : Wiley.

7. Switek, W. and Majewski, T., 1997, Dynamic modelling and optimazation for technology management, *Journal of Computers and Industrial Engineering*, Vol. 33, No. 1-2, pp. 11-14.

8. Tatikonda, L. U. and Tatikonda, M. V., 1994, Tools for cost-effective product design and development, *Journal of Production and Inventory Management*, Second Quarter, pp. 22-28.

9. Troxler, J.W., 1990, Estimating the cost impact of flexible manufacturing, *Journal of Cost Management for the Manufacturing Industry*, Vol. 4, Part 2, pp. 26-32.

40. Vellido, A., Lisboa, P. J. G. and Vaughan, J., 1999, Neural networks in business: a survey of applications (1992-1998), *Journal of Expert Systems with Applications*, Vol. 17, Part 1, pp. 51-70, ISSN: 0957-4174.

41. Wasserman, P. D., 1989, Neural Computing: Theory an Practice, New York: Van Nostrand Reinhold, ISBN: 044-2207433.

42. Widrow, B. and Lehr, M. A., 1990, 30 years of adaptive neural networks: Perceptron, Madaline, and Backpropagation, *Proceedings of the IEEE*, Vol. 78, No. 9, pp. 1415-1442, ISSN: 0018-9219.

43. Yang, S. H., Chung, P. W. H., and Brooks, B. W., 1998, Neural networks based estimation of a semi-batch polymerisation reactor, *Proceedings of the Annual Chinese Automation Conference in the U.K.* pp. 131-136, ISBN: 0953-389006.

44. Zolfaghari, S., and Liang, M., 1998, A simulated annealing approach to machine grouping problem considering processing times and machine capacities, *Proceedings of 6th Industrial Engineering Research Conference*, CH. 168, pp. 228-233.

45. Zurada, J. M., 1992, Introduction to Artificial Neural Systems, St. Paul, MN: West, ISBN: 0314933913.

Published papers

Stockton, D. J. and Wang, Q., 1999, Applying advanced modelling techniques to cost estimating, *Conference of Association of Cost Engineers: Engineering Manufacturing Committee*, March, De Monfort University.

Wang, Q. and Stockton, D. J., 1999, Process time estimating using neural networks, *Proceeding of 15th International Conference in Computer-Aided Production Engineering*, Durham University, April, pp. 201-206, ISBN: 0-9535558-0-1.

Baguley, P., Wang, Q. and Stockton, D. J., 2000, A soft computing approach to cost estimating, *International Conference on Recent Advances in Soft Computing 2000*, June, De Montfort University, Leicester.

Baguley, P., Wang, Q. and Stockton, D. J., 2000, Applied Advanced cost estimating techniques for manufacturing process, *Proceeding of the Seventeenth Conference of the Irish Manufacturing Committee,* August, Ireland, pp. 335-340, ISBN: 0-953-8974-0-0.

Wang, Q., Stockton, D. J. and Baguley, P., 2000, Using neural networks in cost model development process, *Proceedings of the Sixteenth National Conference on Manufacturing Research,* September, University of East London, pp. 59-63, ISBN: 1-86058-267-2.

Wang, Q., Stockton, D. J. and Baguley, P., 2000, Process cost modelling using neural networks, *International Journal of Production Research*, Vol. 38, No. 16, pp. 3811-3821, ISSN: 0020-7543.